CASUALTY ACTUARIAL SOCIETY FORUM

Winter 1999

Including the Ratemaking Discussion Papers and Data Management/Quality/ Technology Call Papers

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The Casualty Actuarial Society *Forum*

Winter 1999 Edition

Including the Ratemaking Call Papers and Data Management/ Quality/Technology Call Papers

To CAS Members:

This is the Winter 1999 Edition of the Casualty Actuarial Society *Forum*. It contains four Ratemaking Discussion Papers, eight Data Management/Quality/Technology Call Papers, and four additional papers.

The Casualty Actuarial Society *Forum* is a non-refereed journal printed by the Casualty Actuarial Society. The viewpoints published herein do not necessarily reflect those of the Casualty Actuarial Society.

The CAS *Forum* is edited by the CAS Committee for the Casualty Actuarial Society *Forum*. Members of the committee invite all interested persons to submit papers on topics of interest to the actuarial community. Articles need not be written by a member of the CAS, but the paper's content must be relevant to the interests of the CAS membership. Members of the Committee for the Casualty Actuarial Society *Forum* request that the following procedures be followed when submitting an article for publication in the *Forum*:

1. Authors should submit a camera-ready original paper and two copies.
2. Authors should not number their pages.
3. All exhibits, tables, charts, and graphs should be in original format and camera-ready.
4. Authors should avoid using gray-shaded graphs, tables, or exhibits. Text and exhibits should be in solid black and white.
5. Authors should submit an electronic file of their paper using a popular word processing software (e.g., Microsoft Word and WordPerfect) for inclusion on the CAS Web Site.

The CAS *Forum* is printed periodically based on the number of call paper programs and articles submitted. The committee publishes two to four editions during each calendar year.

All comments or questions may be directed to the Committee for the Casualty Actuarial Society *Forum*.

Sincerely,

Janet G. Lockwood

Janet G. Lockwood, CAS *Forum* Chairperson

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The 1999 CAS Ratemaking Discussion Papers and Data Management/Quality/Technology Call Papers Presented at the 1999 Ratemaking Seminar March 11-12, 1999 Opryland Hotel Nashville, Tennessee

The Winter 1999 Edition of the CAS *Forum* is a cooperative effort between the CAS *Forum* Committee and two CAS Research and Development Committees: the Committee on Ratemaking and the Committee on Management Data and Information.

The CAS Committee on Ratemaking presents for discussion four papers prepared in response to its Call for 1999 Ratemaking Discussion Papers. In addition, the Committee on Management Data and Information presents eight papers submitted in response to the 1998 Call for Data Management/Quality/Technology Papers.

This Forum includes papers that will be discussed by the authors at the 1999 CAS Seminar on Ratemaking, March 11-12, in Nashville, Tennessee.

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Table of Contents

Workers' Compensation Managed Care Pricing Considerations

Brian Z. Brown, FCAS, MAAA, and
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CASUALTY ACTUARIAL SOCIETY

CALL FOR PAPERS

ABSTRACT

Title: WORKERS' COMPENSATION MANAGED CARE PRICING CONSIDERATIONS

Workers' Compensation insurers have instituted significant managed care initiatives over the last 3 to 5 years. Savings can be significant. Due to the potential savings from managed care initiatives, it is important to reflect managed care in pricing workers' compensation products.

The impact of managed care on insurer loss costs may vary dramatically depending on the type of product and the layer of coverage. Managed care will effect primary carries different than excess carries, since a managed care program will likely effect both the:

- Average cost per claim; and
- The distribution of these costs.

This paper briefly describes managed care initiatives including fee discounts, utilization review, case management and capitated arrangements. It also discusses how managed care can be factored into actuarial pricing methodologies for both the primary layer and excess layers.

WORKERS' COMPENSATION MANAGED CARE

PRICING CONSIDERATIONS

Workers' Compensation insurers have instituted significant managed care (MC) initiatives over the last 3 to 5 years. Initial MC studies indicated savings between 7% and 60%[1]. Savings from future MC expansion will probably be far less than 60% because the base period already includes substantial MC activities[2]. Future MC savings can, however, still be significant, with savings of 10% to 15% not uncommon. Due to the potential savings from MC initiatives, it is important to reflect MC in pricing workers' compensation products.

The impact of MC on insurer loss costs may vary dramatically depending on the type of product and the layer of coverage. The early 1990's saw an explosion in the number of high deductible workers' compensation policies offered and sold. With a high deductible policy, the insured is financially responsible for the primary layer of coverage (e.g., the first $500,000 of loss and possibly ALAE) and the insurer is financially responsible only for loss in excess of the primary retention. For high deductible policies, MC will impact the insurer's loss costs differently than MC will impact the primary loss costs or a primary insurer's loss costs.

This paper will:

[1] See Brian Brown and Melodee Saunders "Recent Trends in Workers' Compensation Coverage", CAS Forum, Summer 1996, page 21.

[2] If claim handlers are simply bill payers and a comprehensive managed care program was introduced to the process, then substantial savings could be achieved. If claim handlers are adeptly performing their duties and applying managed care techniques, then new or enhanced programs will likely have a lesser impact.

- Briefly describe MC initiatives;
- Discuss how MC can be factored into actuarial pricing methodologies for primary layers; and
- Discuss how MC can be factored into pricing excess layers and suggest a method for adjusting excess ratios.

MC INITIATIVES

Some of the more commonly used MC procedures include fee discounts, utilization review, case management and capitated arrangements. These MC procedures will affect large claims and small claims differently. Therefore, excess insurers need to reflect the impact on large claims, while primary insurers will need to reflect the impact on all claims.

1. **Fee Discounts**

   One program that insurers have been using for years to reduce loss costs is fee discounts. Insurers with significant bargaining power are frequently able to negotiate reduced medical fees from a particular medical provider in return for the commitment to channel a large number of injured workers to that provider. Recently, insurers have pursued more aggressive (e.g., larger) discounts. The impact of these discounts varies by the type of claim.

While all claims receive the discount, the impact may be slightly greater for smaller claims. This is due to the fact that historically, for permanent total claims, insurers were already seeking discounts for lifetime care plans. Therefore, aggressive fee discounts were already being pursued for severe claims. For example, if the fee discount is 10% for all claims, a 15% impact may apply to primary losses but a lower number would apply to excess losses.

2. **Utilization Review (UR)**

Insurers using UR have employees or subcontractors review the procedures and practices of physicians to determine if appropriate medical treatments are being utilized. Proposed medical procedures are evaluated and authorization is given only when deemed medically necessary. The three utilization review techniques most frequently used are concurrent review, retrospective review and pre-admission certification. Concurrent reviews are designed to immediately recognize inappropriate treatment patterns and alter the healthcare services being provided for a worker. This type of review often centers on the length of stay for a hospital admission. Retrospective reviews are designed to detect errors in past treatment. These errors can then be brought to the attention of the providers in an effort to curb inappropriate or excessive care. Pre-admission certifications are used to direct patients away from costly inpatient care to outpatient services when appropriate. UR should impact small and medium size claims to a greater extent than very large claims. For large claims, most insurers were already performing UR type procedures.

3. **Case Management**

Case management involves a qualified professional (usually a nurse) overseeing the progress of an injured employee to assure appropriate and timely care. Case managers will typically work closely with all parties involved (employees, employer and physicians) to get the injured employee back to work as quickly as possible even if the employee's job duties need to be refined.

Case management is expected to:

- Reduce the overall cost of all claims (except for medical-only and fatalities); and
- Reduce the frequency of large claims (e.g., permanent total) as some workers will return to work quicker than in the past (due to light duty assignments).

Additionally, case management can reduce indemnity costs, as there is an emphasis on return to work.

4. **Capitated Arrangements**

In a capitated arrangement, the healthcare provider receives a flat fee. In exchange, the healthcare provider agrees to provide appropriate medical services for all injured workers they treat, subject to their contract with the insurer during a certain time period. Typically, claims occurring outside the state are excluded and for catastrophic claims, the medical treatment costs have a predetermined dollar limit.

These arrangements are expected to reduce medical costs. The insurers have essentially transferred much of the predictable expense to a MC organization. This arrangement may effect smaller and medium size claims more than large claims, as medical payments above thresholds are not covered. (For the large claims, once a threshold is exceeded the payment mechanism switches to fee for services.)

PRICING REFLECTING MC - PRIMARY LAYER

In reflecting MC in pricing, it is important to segregate the data subsequent to and prior to MC. For example, assume we are analyzing the following data. The assumption underlying the data is that pure premiums are trending at 6% per year and MC has a one-time impact of 10% in 1996.[3]

Table 1

Policy Year	Developed Pure Premium	Annual Implied Trend
1993	2.00	
1994	2.12	6.0
1995	2.25	6.0
1996*	2.15	(4.4)
1997	2.28	6.0
1993-97		3.3

* Implemented comprehensive MC program with expected savings equal to 10%

[3] We have assumed that MC is fully effective on 1/1/96. MC would typically be phased in over a period of time in a state and may take a year or longer to be fully effective. This phase in makes it more difficult to separately estimate the trend and MC effect.

Without appropriately measuring the MC impact, pricing errors could occur. For example, it would be incorrect to simply trend the previous policy years to a 1998 level based on a historical average trend rate of 3.3% and apply a 10% MC discount.

The following table displays this **incorrect** calculation:

Table 2

(1) Policy Year	(2) Developed Pure Premium	(3) Trend to 1998*	(4) Managed Care Credit	(5) Projected 1998 Pure Premium
1993	2.00	1.176	0.9	2.12
1994	2.12	1.138	0.9	2.17
1995	2.25	1.102	0.9	2.23
1996	2.15	1.067	0.9	2.06
1997	2.28	1.033	0.9	2.12
Average				2.14

* at 3.3%

In the above example, MC savings are counted twice: the credit from column (4) of the above table, as well as the lower trend rate derived from Table 1, where MC savings are already reflected in policy years 1996 and 1997. To avoid the double counting of savings, we should perform the analysis after removing the one time impact of MC and reflect the MC impact after adjusting the pure premium to a 1998 level:

Table 3				
Policy Year	**Developed Pure Premium**	**Adjustment to Remove Managed Care**	**Adjusted Pure Premium**	**Implied Trend**
1993	2.00	1.0	2.00	
1994	2.12	1.0	2.12	6%
1995	2.25	1.0	2.25	6
1996	2.15	1.11	2.39	6
1997	2.28	1.11	2.53	6

The following approach can then be used to calculate the 1998 pure premium:

Table 4					
Policy Year	**Adjusted Pure Premium**	**Trend to 1998**	**Projected Adjusted* 1998 Pure Premium**	**Managed Care Credit**	**Adjusted 1998 Pure Premium**
1993	2.00	1.34	2.68	0.9	2.41
1994	2.12	1.26	2.68	0.9	2.41
1995	2.25	1.19	2.68	0.9	2.41
1996	2.39	1.12	2.68	0.9	2.41
1997	2.53	1.06	2.68	0.9	2.41
Average					2.41

* Prior to MC

Thus, the first approach which incorrectly uses experience both before and after MC to determine a trend factor and then applies the 10% MC reduction understates the 1998 pure premium by 11.2% (2.14 from Table 2 versus 2.41 from Table 4). As a note, if the more recent years are relied on more heavily and 2.09 is selected as the projected 1998 pure premium (average of 1996 and 1997) the understatement is more severe at 13.3% (see Table 2).

Also, if the 0.9 MC adjustment was not made in the first set of calculations (Table 2), the selected pure premium would be 2.38 and would be deficient by about 1.2%. Therefore, in pricing workers' compensation coverage, it is important to identify the MC impacts in the data versus the MC savings that are expected to come in the future.

For example, if an additional MC program will be introduced in 1998 in state X, and based on analyzing state Y data where the program was introduced 2 years ago we observed savings of 5%, then we could reduce the 1998 pure premium by 5% in state X (assuming the same impact in state X as state Y). However, if the program was instituted in state X in 1996 and is already reflected in our ratemaking data, which reflects trending procedures, then it would be incorrect to simply reduce our 1998 indication by 5%.

An added difficulty in performing the above analysis is that different MC initiatives may be introduced at different points in time. Also, the data will not display trends as clearly as this hypothetical data.

There are several ways to measure MC savings. One way is to evaluate claims before the introduction of MC (adjusted to current cost levels) and after the introduction of MC (again adjusted to current cost level). A simplistic approach may involve measuring average severities (assuming no frequency impact). Using the example above, where MC was introduced in 1996, we may have observed the following severities:

Table 5			
(1) **Policy Year**	**(2)** **Average Severity**	**(3)** **Trend Factor to 1998**	**(4)** **Current Cost Level Severity** **(2)x(3)**
1993	2,500	1.34	3,350
1994	2,650	1.26	3,339
1995	2,809	1.19	3,343
1996	2,680	1.12	3,002
1997	2,840	1.06	3,010
(5) Average Severity	1993 - 1995 = 3,344		
(6) Average Severity	1996 - 1997 = 3,006		
(7) Managed Care Impact (1-(6)/(5)) = 10%			

This approach assumes a 6% trend factor affects each year. A more refined approach might vary the trend factor in each calendar year; however, the general framework would be the same.

The above examples are intended to illustrate the interaction between the loss cost trend and MC. To accurately measure MC savings, it is necessary to accurately measure the annual loss costs trend. Measuring the effect of trend separate from MC is difficult. In order to determine the underlying claim cost trend, one needs to make an adjustment for the MC impact. Yet in order to determine the MC impact, one needs to know the underlying trend factor so that all years can be adjusted to a comparable basis. Therefore, when measuring the effect of MC separate from trend:

- economic models can be developed;
- individual claim studies can be performed, and/or
- assumptions and judgement must be utilized.

MEASURING MANAGED CARE IMPACTS

The effects of MC can be estimated by using an actuarial, clinical, or claims perspective. Using an actuarial perspective, key aggregate statistics should be reviewed. These statistics should be analyzed before and after the implementation of MC. Some of the statistics include, but are not limited to the following:

- Paid severities;
- Incurred severities;
- Loss ratios;
- Pure premiums;
- Percentage of medical-only claims;
- Claim frequencies;

- Average days off work; and
- Report lags.

Analysis of average paid and incurred severities is relatively straightforward. Severities with and without MC are analyzed (after being adjusted to current cost and benefit levels) and the reduction in severities is attributable to MC.

Similarly, we could analyze pure premiums or loss ratios (adjusted to current cost levels and for premium credits and debits). As a note, it would be preferable if we could identify MC and non-MC claims in a state during the same time period. This will happen sometimes, for example, if the insured can select MC as an option. If a single time period is used, issues related to claim cost inflation and benefit changes are eliminated.

Many MC initiatives focus on early intervention by case managers. It is believed that if the case manager can impact treatment within a day or two after the injury date, then savings can result. With the case manager's focus on return to work, we would expect more injured workers to return to work within the waiting period (generally three to seven days). Therefore, if the percentage of medical-only claims is increasing it is a sign that MC initiatives are working. We can estimate the MC impact by weighting average severities by type of claim.

Assume we have the following distribution of claims and severity by type of claim:[4]

Table 6		
Type of Claim	**Total Average Cost**	**Distribution of Claims**
Medical-only	625	63.63%
Minor/TT	5,084	32.75
PT/Major	102,784	3.55
Fatal	95,372	0.07
Average	5,778	100.00%

The severities are displayed in a paper by Mr. William R. Gillam and are part of the NCCI excess loss rating methodology. As a note, Mr. Gillam's paper did not include a medical-only severity; therefore, we selected a medical-only severity of $625.

If the medical-only percentage increases from 63.63% to 66.63% due to case manager/early intervention and we expect this to reduce the Minor/TT category from 32.75% to 29.75%, then we would anticipate the average severity to decrease to $5,645 with the new weights (assuming the medical-only severity remains constant). Thus a 3% increase in medical-only claims reduces severities or has a MC impact of 2.4%.

As a note, the above percentage only measures the impact of early intervention. If we estimated that other MC initiatives reduced severity by 10%, then we would estimate a combined MC impact of 1 - (.9)(1 - .024) or 12.2%.

[4] William R. Gillam, "Retrospective Rating: Excess Loss Factors", FCAS LXXVIII 1991 p.1

Similarly, if we estimated that MC initiatives will get employees back to work quicker, this initiative will affect the distribution of claims by injury type. For example, with light duty assignments and aggressive case management, the percentage of PT/Major claims may decrease with fewer claimants moving from Minor/TT to PT/Major in a MC environment. Therefore, if we assume a 20% decrease in PT/Major claims, the percentage of PT/Major claims decreases from 3.55% to 2.84% while the Minor/TT percentage increases from 32.75% to 33.46%. This decreases the overall severity from $5,778 to $5,085 or approximately 13.6%.

Other statistics which will affect workers' compensation costs are the:

- Number of days off work; and
- Report lags.

As the number of days off work increase, claim costs increase. Therefore, if MC is able to reduce the number of days off work (due to more quickly achieving maximum medical improvement or accelerating the creation of light duty jobs) workers' compensation claim costs will decrease.

Also, decreases in report lags may lead to lower claim costs due to the benefits of early intervention.[5] Therefore, if MC initiatives reduce the report lag, overall claim costs may decrease.

ALTERNATIVE METHODOLOGY

The above mentioned analyses focus on analyzing aggregate claim statistics. Another methodology which measures the impact of MC analyzes individual claim statistics. Under this approach, groups of claims are identified - those in MC and those not treated by MC. It is probably best if both MC and non-MC claims occurred during the same time period; however, this is not essential. The same time period eliminates most, if not all, of the issues related to claim cost inflation and benefit changes. If claims are not from the same time period, the older claims should be adjusted for claim cost inflation and benefit level changes.

In this approach, the total amount of paid loss (or incurred loss if MC does not affect case reserve adequacy) on each claim at a selected maturity (e.g., a study at year-end 1997 might use payments through 24 months for all claims occurring during 1995) is treated as the dependent variable in a regression equation. Independent variables might include body part, nature of injury, age of the claimant, industry group, employer size and the use/non-use of MC. The MC variable then measures the impact of MC.[6]

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[5] One exception to this statement is that the most severe claims are generally reported very quickly and have a very high claim cost.

[6] The MC variable would be a dummy variable with MC claims having a code of 1 and non-MC a code of 0.

CLINICAL AND CLAIMS PERSPECTIVE

Insurers' current MC strategies could be analyzed from a clinical perspective and the cost savings quantified. For example, the clinicians could summarize how long employees are out of work or the time duration of medical treatment both with and without the implementation of MC.

MC strategy could also be analyzed from a claims perspective. The claims personnel could quantify the average cost of claims (medical and indemnity separately) with and without the implementation of MC. This study would be based on reviewing individual claim files (most commonly a sample of files). For both the clinical and claims perspective, the analyses should be done by type of claim and MC activity.

PRICING MC - EXCESS LAYERS

We would expect the MC savings impact to vary depending on the:

- Type of the claim; and
- Size of the claim.

This section will discuss some procedures on adjusting the size of loss distributions to account for a MC program.

For illustrative purposes, we will comment on the size of loss procedure used by the National Council on Compensation Insurance (NCCI). Mr. William R. Gillam discusses this procedure in "Retrospective Rating: Excess Loss Factors".[7]

The NCCI procedure combines four different type of claim distributions to estimate excess loss factors (ELF's). The ELF's are used to estimate the charge for limiting losses at a certain dollar amount in the Retrospective Rating Manual. The ELF times the standard premium is the estimated pure loss charge for limiting losses. Thus, if an insurer wrote an excess or a high deductible policy, multiplying the ELF by the standard premium would represent the insurer's loss cost for this coverage.

In estimating the combined loss distribution, NCCI evaluates separate curves for the following claim types:

- Fatalities;
- Permanent total & major permanent partial (PT/Major);
- Minor permanent partial & temporary total (Minor/TT); and
- Medical-only claims.

[7] William R. Gillam, "Retrospective Rating: Excess Loss Factors", FCAS LXXVIII 1991 p.1

The NCCI procedure develops countrywide distributions and the distributions are adjusted for each state based on the state's:

- Average claim size; and
- Mix of Hazard Group exposure by state.

The distributions normalize the claims so that an entry ratio distribution can be developed.

The following table is extracted from Exhibit 3, Part 1 (Fatality Curve) of Mr. Gillam's paper:

Table 7	
Entry Ratio	**Excess Ratio**
0.25	0.804
0.50	0.659
0.75	0.544
1.00	0.452
1.25	0.377
1.50	0.315

Using entry ratios adjusts the excess ratios for the effect of inflation and for differences by state and hazard group.

The interpretation of the 0.25 entry ratio is that if the statewide average severity for fatalities is 100,000, then:

- We would expect 80.4% of the losses to exceed 25,000 (an entry ratio of 0.25 times 100,000); and
- We would expect 31.5% of the losses to exceed 150,000 (an entry ratio of 1.50).

Since we expect MC to alter the severities by type of claim, we would expect MC to also change the ELF's and excess ratios.

The following outlines a procedure for adjusting the excess ratios for MC. It involves adjusting the severities and injury weights by claim type to derive excess ratios adjusted for MC programs.

Assume we are pricing an insured with expected ultimate losses of $50.0 million and we assume that the ELF tables from Mr. Gillam's paper are appropriate to price this risk.[8] For the convenience of the reader, we have reproduced Mr. Gillam's Exhibit 2 as Exhibit 1 in this paper. We will next outline how we expect MC to change Exhibit 1.

Assume we are pricing an excess or large deductible policy for a risk that retains the first $100,000 of loss.

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[8] We are assuming that the ELF table is appropriate before MC and that MC changes the avergae severity by claim type but not the dispersion of individual claims.

Underlying Exhibit 1 are the following assumptions:

- Fatal average cost = $95,372;
- PT/Major average cost = $102,784; and
- Minor/TT average cost = $5,084.

To utilize this procedure we first need an estimate of the total severity split between indemnity and medical costs. Let us assume the following:

Table 8

Type of Claim	Total Average Cost	Medical Component	Indemnity Component
Fatal	$95,372	$19,074	$76,298
PT/Major	102,784	61,670	41,114
Minor/TT	5,084	2,542	2,542

Mr. Gillam did not include medical-only claims. All medical-only claims would most likely be below the deductible and therefore be fully retained by the insured.

Assume that we have measured MC savings in total and by type of loss based on the methods we previously discussed. The savings are as follows[9]:

- Medical savings of 25%; and
- Indemnity savings of 20%.

[9] We selected significant savings percentages for illustration purposes.

These overall savings may likely vary by type of claim:[10]

- **Fatalities** - We would expect that MC will have little impact on future fatality costs. MC is unlikely to change the indemnity portion of fatal claims. MC could have some impact on the medical portion of fatal claims. However, if someone is seriously injured and is near death it is unlikely that MC principles would be employed (e.g., the worker would be transported to the nearest hospital and all procedures possible would be undertaken to save the injured worker's life). Therefore, we would not expect MC to change the average cost or distribution of costs for fatalities.

PT/Major - We would expect MC to have an impact on these claims. If the average indemnity impact for all claims is 20% we would expect the impact for PT/Major indemnity to be less. This is because MC cannot impact the indemnity on some claims (where the claimant will be unable to return to work (e.g., quadriplegic)). Additionally, as we discussed, MC (especially if case management is used) will likely reduce the percentage of PT/Major claims, thereby increasing the average severity on the remaining claims. For illustrative purposes, we have assumed that the MC impact for PT/Major indemnity to be 5%.

[10] We will ignore medical-only claims as we assume that all medical-only claims will be below the deductible and fully retained by the insured. Also we have not assumed that MC will affect the distribution of medical-only claims.

We have also assumed a lower than average impact on the medical claims because some integrated MC programs have probably been in place for these claims. For PT claims, many carriers have already negotiated lifetime care plans for severely injured workers. Therefore the savings due to introducing a more comprehensive program may not be as great as the all claim average. Additionally, the smaller claims are shifting to Minor/TT, which is increasing the average severities on the remaining claims. For this example, we have assumed the medical savings for these claims will be 5.0%.

- **Minor/TT** - MC will most likely impact the severities for these smaller claims, where integrated MC programs may not have been in place for an extended period of time. This group of claims includes some individuals who could have returned to work but were lingerers. Historically, for this category, case management and utilization reviews were not fully employed. Therefore for this group, we have assumed a savings of 8.0% for the indemnity component and a savings of 20.0% for the medical component.

Using the above mentioned savings with the statewide average severities listed in Table 8 results in the following severities subsequent to the introduction of MC.

Table 9			
Type of Claim	**Total**	**Medical Component**	**Indemnity Component**
Fatal			
Before MC	95,372	19,074	76,298
After MC	95,372	19,074	76,298
PT/Major			
Before MC	102,784	61,670	41,114
After MC [1]	97,645	58,587	39,058
Minor/TT			
Before MC	5,084	2,542	2,542
After MC [2]	4,373	2,034	2,339

1) Assumes 5.0% medical savings and 5.0% indemnity savings
2) Assumes 20.0% medical savings and 8.0% indemnity savings

Additionally, due to a strong case management program, we can assume that the percentage of claims which are PT/major decrease from 3.55% to 2.84% (a 20% effect) and these claims move from PT/major to minor/TT (i.e., moves from 32.75% to 33.46%).

Therefore the effect of MC is displayed below[11]:

	Table 10			
	Injury Weight[12]		**Severity**	
Types of Claims	**Before MC**	**After MC**	**Before MC**	**After MC**
Medical-only	6.9%	8.5%	625	625
PT/Major	63.1	59.0	102,784	97,645
Minor/TT	28.8	31.1	5,084	4,373
Fatalities	1.2	1.4	95,372	95,372
Total			5,778	4,701

[11] Note that we need to reweight the excess ratios by type of claim due to a shift in frequencies and severities.
[12] The number of claims for each injury type are needed to perform the calculation.

Thus, MC reduces the average severity from 5,778 to 4,701 or 18.6%.

We can also use Mr. Gilliam's framework to determine the effect of MC on the excess loss distributions.

Exhibit 1 displays the excess ratio (portion of total losses expected to exceed the retention) at $100,000 of 18.4% prior to MC. With expected total losses of $50.0 million, the expected excess loss pure premium would total approximately $9.2 million.

However, taking into account the MC adjustments mentioned above results in an excess ratio of 16.6% (the calculation is described below) or a loss cost provision of approximately $6.62 million, for a difference of about 28.0% or $2.58 million.

Exhibit 1 from Mr. Gillam's paper can be adjusted for MC based on the above mentioned parameters. The calculations are similar for each loss type; therefore, we will only discuss the calculation for PT/major.

Exhibit 2 displays the revised calculation. Column (1) displays the loss limit. Column (6) displays the entry ratio for PT/Major. The entry ratio is equal to:

- The loss limit; divided by

- 1.1; divided by
- The average severity.

Dividing the loss limit by 1.1 is intended to adjust the excess ratios from a per-claim to a per-occurrence basis and is discussed in Mr. Gillam's paper on page 6. Next, the quotient is divided by the average severity to convert the claim size to an entry ratio. With MC, the PT/Major severity decreases from $102,784 to $97,645. Thus, the entry ratio at a loss limit of $100,000 increases from 0.88 to 0.93. This revised entry ratio changes the excess ratio (Column (8)) from 0.284 to 0.271.

Column (7) displays the injury weight on the losses for PT/Major relative to total losses. The injury weights are used to weight the excess ratios by type of claim to derive an all claim excess ratio.

We assumed that MC would reduce the PT/Major injury weight from 63.1% to 59.0%. Column (9) displays the partial excess ratio for PT/Major (which is the revised injury weight multiplied by the revised excess ratio). The partial excess ratios are then summed by loss limit to determine the all claims excess ratios (as shown in Column (14)).

Before MC the all claims excess ratio at 100,000 was 18.4%. After the above mentioned MC adjustments the revised all claims excess ratio is 16.6%. Additionally MC reduces total losses from $50 million to $40 million (20% reduction).

The reduction in excess ratios is largely due to:

- A shift in claims from PT/Major to Minor/TT (the PT/Major excess ratios are higher than the Minor/TT excess ratios); and
- A lower severity for most claims which results in larger entry ratios and lower excess ratios.

Somewhat offsetting these two factors is the significant decrease in minor/TT claim costs which results in giving more weight to the fatal excess ratios.

SUMMARY

Insurers have recently instituted more aggressive MC programs for workers' compensation claims. These include more comprehensive fee discounts, utilization review, case management and capitated arrangements. It is important to appropriately measure MC savings so MC can be reflected in insurers' pricing. This paper has outlined some pitfalls in measuring MC savings. MC programs will also effect both the:

- Average cost per claim; and
- Distribution of these costs.

The effects of the MC programs will vary by type of program and by type and size of claim. MC programs will separately affect indemnity costs and medical costs and have different impacts on primary layers of losses and excess layers. Insurers and reinsurers who price primary and excess layers of workers' compensation need to properly factor in the impact of MC.

EXHIBIT 1

National Council on Compensation Insurance
State M
Effective 01/01/89
Limited Fatal Benefits - Nonescalating PT/Major Benefits
Excess Loss Factors Calculation
Hazard Group II

	Fatal				PT/Major				Minor/TT				
(1) Loss Limit	(2) Ratio to Avg / 1.1 (Entry Ratio)	(3) Injury Wgt	(4) Excess Ratio	(5) Excess Ratio x Inj Wgt	(6) Ratio to Avg / 1.1 (Entry Ratio)	(7) Injury Wgt	(8) Excess Ratio	(9) Excess Ratio x Inj. Wgt	(10) Ratio to Avg / 1.1 (Entry Ratio)	(11) Injury Wgt	(12) Excess Ratio	(13) Excess Ratio x Inj. Wgt	(14) Average Excess Ratio
$ 10,000	0.10	**0.011**	0.908	0.010	0.09	**0.631**	0.910	0.575	1.79	**0.288**	0.361	0.104	0.689
15,000	0.14		0.874	0.010	0.13		0.870	0.549	2.68		0.223	0.064	0.624
20,000	0.19		0.834	0.010	0.18		0.820	0.518	3.58		0.138	0.040	0.567
25,000	0.24		0.796	0.009	0.22		0.780	0.493	4.47		0.085	0.024	0.526
30,000	0.29		0.760	0.009	0.27		0.730	0.461	5.36		0.053	0.015	0.485
35,000	0.33		0.733	0.008	0.31		0.690	0.436	6.26		0.034	0.010	0.454
40,000	0.38		0.700	0.008	0.35		0.650	0.410	7.15		0.022	0.006	0.425
50,000	0.48		0.640	0.007	0.44		0.562	0.355	8.94		0.010	0.003	0.365
75,000	0.71		0.521	0.006	0.66		0.387	0.244	13.41		0.002	0.001	0.251
100,000	**0.95**		**0.422**	**0.005**	**0.88**		**0.284**	**0.179**	**17.88**		**0.000**	**0.000**	**0.184**
125,000	1.19		0.342	0.004	1.11		0.220	0.139	22.35		0.000	0.000	0.143
150,000	1.43		0.278	0.003	1.33		0.181	0.114	26.82		0.000	0.000	0.117
175,000	1.67		0.226	0.003	1.55		0.153	0.097	31.29		0.000	0.000	0.099
200,000	1.91		0.184	0.002	1.77		0.132	0.083	35.76		0.000	0.000	0.085
225,000	2.14		0.151	0.002	1.99		0.116	0.073	40.23		0.000	0.000	0.075
250,000	2.38		0.123	0.001	2.21		0.103	0.065	44.70		0.000	0.000	0.066
275,000	2.62		0.101	0.001	2.43		0.093	0.059	49.17		0.000	0.000	0.060
300,000	2.86		0.082	0.001	2.65		0.085	0.054	53.64		0.000	0.000	0.055
325,000	3.10		0.067	0.001	2.87		0.077	0.049	58.11		0.000	0.000	0.049
350,000	3.34		0.055	0.001	3.10		0.071	0.045	62.58		0.000	0.000	0.045
375,000	3.57		0.045	0.001	3.32		0.066	0.042	67.06		0.000	0.000	0.042
400,000	3.81		0.037	0.000	3.54		0.062	0.039	71.53		0.000	0.000	0.040
425,000	4.05		0.031	0.000	3.76		0.058	0.037	76.00		0.000	0.000	0.037
450,000	4.29		0.025	0.000	3.98		0.054	0.034	80.47		0.000	0.000	0.034
475,000	4.53		0.021	0.000	4.20		0.051	0.032	84.94		0.000	0.000	0.032
500,000	4.77		0.017	0.000	4.42		0.048	0.030	89.41		0.000	0.000	0.031
600,000	5.72		0.008	0.000	5.31		0.039	0.025	107.29		0.000	0.000	0.025
700,000	6.67		0.004	0.000	6.19		0.033	0.021	125.17		0.000	0.000	0.021
800,000	7.63		0.002	0.000	7.08		0.029	0.018	143.05		0.000	0.000	0.018
900,000	8.58		0.001	0.000	7.96		0.025	0.016	160.93		0.000	0.000	0.016
1,000,000	9.53		0.000	0.000	8.84		0.023	0.015	178.81		0.000	0.000	0.015
2,000,000	19.06		0.000	0.000	17.69		0.011	0.007	357.63		0.000	0.000	0.007
3,000,000	28.60		0.000	0.000	26.53		0.007	0.004	536.44		0.000	0.000	0.004
4,000,000	38.13		0.000	0.000	35.38		0.005	0.003	715.26		0.000	0.000	0.003
5,000,000	47.66		0.000	0.000	44.22		0.004	0.003	894.07		0.000	0.000	0.003
6,000,000	57.19		0.000	0.000	53.07		0.003	0.002	1,072.88		0.000	0.000	0.002
7,000,000	66.72		0.000	0.000	61.91		0.003	0.002	1,251.70		0.000	0.000	0.002
8,000,000	76.26		0.000	0.000	70.76		0.002	0.001	1,430.51		0.000	0.000	0.001
9,000,000	85.79		0.000	0.000	79.60		0.002	0.001	1,609.33		0.000	0.000	0.001
10,000,000	95.32		0.000	0.000	88.45		0.002	0.001	1,788.14		0.000	0.000	0.001

Fatal Average Cost per Case 95,372
PT/Major Average Cost per Case 102,784
Minor/TT Average Cost per Case 5,084

Note - Any differences from Mr. Gillam's paper are due to rounding.

EXHIBIT 2 - Effect of Managed Care Savings

National Council on Compensation Insurance
State M
Effective 01/01/89
Limited Fatal Benefits - Nonescalating PT/Major Benefits
Excess Loss Factors Calculation
Hazard Group II

	Fatal				PT/Major				Minor/TT				
(1) Loss Limit	(2) Ratio to Avg / 1.1 (Entry Ratio)	(3) Injury Wgt	(4) Excess Ratio	(5) Excess Ratio x Inj. Wgt	(6) Ratio to Avg / 1.1 (Entry Ratio	(7) Injury Wgt	(8) Excess Ratio	(9) Excess Ratio x Inj. Wgt	(10) Ratio to Avg / 1.1 (Entry Ratio)	11) Injury Wgt	(12) Excess Ratio	(13) Excess Ratio x Inj. Wgt	(14) Average Excess Ratio
$ 10,000	0.10	**0.014**	0.908	0.013	0.09	**0.590**	0.906	0.534	2.08	**0.311**	0.316	0.098	0.646
15,000	0.14		0.874	0.012	0.14		0.862	0.509	3.12		0.182	0.057	0.578
20,000	0.19		0.834	0.012	0.19		0.812	0.479	4.16		0.104	0.032	0.523
25,000	0.24		0.796	0.011	0.23		0.767	0.452	5.20		0.059	0.018	0.482
30,000	0.29		0.760	0.011	0.28		0.717	0.423	6.24		0.034	0.011	0.445
35,000	0.33		0.733	0.010	0.33		0.675	0.398	7.28		0.020	0.006	0.415
40,000	0.38		0.700	0.010	0.37		0.631	0.373	8.32		0.014	0.004	0.387
50,000	0.48		0.640	0.009	0.47		0.544	0.321	10.39		0.007	0.002	0.332
75,000	0.71		0.521	0.007	0.70		0.371	0.219	15.59		0.001	0.000	0.226
100,000	**0.95**		**0.422**	**0.006**	**0.93**		**0.271**	**0.160**	**20.79**		**0.000**	**0.000**	**0.166**
125,000	1.19		0.342	0.005	1.16		0.210	0.124	25.99		0.000	0.000	0.129
150,000	1.43		0.278	0.004	1.40		0.172	0.102	31.18		0.000	0.000	0.106
175,000	1.67		0.226	0.003	1.63		0.145	0.086	36.38		0.000	0.000	0.089
200,000	1.91		0.184	0.003	1.86		0.125	0.074	41.58		0.000	0.000	0.077
225,000	2.14		0.151	0.002	2.09		0.110	0.065	46.77		0.000	0.000	0.067
250,000	2.38		0.123	0.002	2.33		0.098	0.058	51.97		0.000	0.000	0.059
275,000	2.62		0.101	0.001	2.56		0.088	0.052	57.17		0.000	0.000	0.054
300,000	2.86		0.082	0.001	2.79		0.080	0.047	62.37		0.000	0.000	0.048
325,000	3.10		0.067	0.001	3.03		0.073	0.043	67.56		0.000	0.000	0.044
350,000	3.34		0.055	0.001	3.26		0.067	0.040	72.76		0.000	0.000	0.040
375,000	3.57		0.045	0.001	3.49		0.063	0.037	77.96		0.000	0.000	0.038
400,000	3.81		0.037	0.001	3.72		0.059	0.035	83.15		0.000	0.000	0.035
425,000	4.05		0.031	0.000	3.96		0.054	0.032	88.35		0.000	0.000	0.033
450,000	4.29		0.025	0.000	4.19		0.051	0.030	93.55		0.000	0.000	0.031
475,000	4.53		0.021	0.000	4.42		0.048	0.028	98.75		0.000	0.000	0.029
500,000	4.77		0.017	0.000	4.68		0.046	0.027	103.94		0.000	0.000	0.027
600,000	5.72		0.008	0.000	5.59		0.037	0.022	124.73		0.000	0.000	0.022
700,000	6.67		0.004	0.000	6.52		0.032	0.019	145.52		0.000	0.000	0.019
800,000	7.63		0.002	0.000	7.45		0.027	0.016	166.31		0.000	0.000	0.016
900,000	8.58		0.001	0.000	8.38		0.024	0.014	187.10		0.000	0.000	0.014
1,000,000	9.53		0.000	0.000	9.31		0.022	0.013	207.89		0.000	0.000	0.013
2,000,000	19.06		0.000	0.000	18.62		0.011	0.006	415.77		0.000	0.000	0.006
3,000,000	28.60		0.000	0.000	27.93		0.007	0.004	623.66		0.000	0.000	0.004
4,000,000	38.13		0.000	0.000	37.24		0.005	0.003	831.55		0.000	0.000	0.003
5,000,000	47.66		0.000	0.000	46.55		0.004	0.002	1,039.44		0.000	0.000	0.002
6,000,000	57.19		0.000	0.000	55.86		0.003	0.002	1,247.32		0.000	0.000	0.002
7,000,000	66.72		0.000	0.000	65.17		0.003	0.002	1,455.21		0.000	0.000	0.002
8,000,000	76.26		0.000	0.000	74.48		0.002	0.001	1,663.10		0.000	0.000	0.001
9,000,000	85.79		0.000	0.000	83.79		0.002	0.001	1,870.99		0.000	0.000	0.001
10,000,000	95.32		0.000	0.000	93.10		0.002	0.001	2,078.87		0.000	0.000	0.001

Fatal Average Cost per Case	95,372
PT/Major Average Cost per Case	97,645
Minor/TT Average Cost per Case	4,373

Something Old, Something New in Classification Ratemaking With a Novel Use of GLMs for Credit Insurance

Keith D. Holler, FCAS, MAAA, ASA, ARM,
David Sommer, FCAS, MAAA, and
Geoff Trahair, BEc(Hons), FIAA, FIA

Something Old, Something New in Classification Ratemaking With a Novel Use of GLMs for Credit Insurance

Abstract:

This paper discusses some methods that can be used to calculate classification relativities and reduce the error that would otherwise occur by using one-way analysis. Section 2 will discuss the problem of risk classification analysis from a mathematical and statistical viewpoint and show some of the implied solutions from these approaches. This exposition revisits the work pioneered in the USA by Bailey, Bailey and Simon, and Brown, which are the foundations of American casualty practice in the area of classification ratemaking. We will then revisit another technique based on Generalized Linear Modeling (GLM) in Section 3 and discuss the advantages of implementing this technique. For those who have a strong background in classification ratemaking and GLM, we recommend skipping to Sections 4 and 5, where we present an application of this technique to credit insurance and discuss the results.

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TABLE OF CONTENTS

TABLE OF CONTENTS

Section 1. Introduction

1.1 Description of the General Problem

A premium rating plan has two goals. First, it should ensure that the insurer receives premiums at a level which is expected to be adequate to cover losses and expenses, while providing a fair rate of return. Second, it should allocate those premiums fairly between insureds, where "fairly" means that higher premiums are paid by those insureds with greater risk of loss and vice-versa, while all insureds contribute consistently to profit and expense. While we recognize that there may be considerations in which an insurer chooses not to price a risk with respect to these goals (regulatory, competitive, etc.), we will assume, for the purposes of this paper, that these other considerations are addressed subsequent to determining the expected value premiums.

To meet these goals, most ratemaking consists of two aspects. The first is the determination of the overall rate level. This addresses the first goal mentioned above. The second aspect of ratemaking is the risk classification analysis. It is through the risk classification plan and its rate relativities that the second goal of equity is installed in the pricing process.

In determining classification relativities, it appears simple enough to analyze loss costs (loss per exposure) by variable to calculate the necessary factors. If married drivers have half of the loss cost of unmarried drivers, they should receive a relativity of 0.5 and so on. This single-variable analysis, however, makes an assumption that is generally not true - that the effects of a single variable are independent of all other rating variables. We introduce the following example[1] which appears in the SAS/STAT manual [1] to show some of the difficulty with this assumption.

1.2 A Simple Example

Consider claim count data which are *modeled* using two classification variables: age group, with two levels; and car type, with three levels. The claim counts and exposures for each of the classes are as follows:

Claims

Age Group	Car Size		
	Large	Medium	Small
1	1	37	42
2	14	73	101

Exposures

Age Group	Car Size		
	Large	Medium	Small
1	100	1200	500
2	300	500	400

Actual Frequency

Age Group	Car Size		
	Large	Medium	Small
1	.010	.031	.084
2	.047	.146	.253

Frequency Relativities

Age Group	Car Size		
	Large	Medium	Small
1	1.0	3.1	8.4
2	4.7	14.6	25.3

The actual frequency for a class is computed as the number of claims divided by the number of exposures for that class. Each class is a combination of values for each classification variable (e.g. - age group 1 with a large car). The observed relativities in this example are

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1 Reprinted with permission: SAS Institute Inc., SAS® Technical Report P-243, SAS/STAT® Software: The GENMOD Procedure, Release 6.09, Cary, NC: 1993, Copyright© SAS Insitute Inc. 88 pp.

computed using claim frequency. (This approach assumes that the average claim size is the same for each class.) In addition, the large car size/age group one (L1) class is assumed to be the 'base class', which has a relativity of 1.0. The observed relativity of 25.3 for the small car size/age group two (S2) class means that for each S2 car, we observed 25.3 times as many claims on average than for each L1 car. If the base rate (i.e. the premium rate for a single L1 car) is $100, the premium charged for a single S2 car would be $2,530 or 25.3 x $100.

One Way Method

Class	Claims	Exposures	Frequency	Relativity
Large car size	15	400	.038	1.000
Medium car size	110	1700	.065	1.725
Small car size	143	900	.159	4.237
Age Group 1	80	1800	.044	1.000
Age Group 2	188	1200	.157	3.525

The one-way method computes a relativity separately for each value of the car size variable and the age group variable. For example, based on this method, the relativity for a medium sized car is .065/.038, or 1.725, where .038 is the total frequency for the base car size, large. Note that all of the data is used to determine the car size relativities and then used again to determine the age group relativities.

The final overall rating class (car size/age group) relativity is then the product of the individual car size relativity and the individual age group relativity. For example, the S2 relativity based on the one-way method would be 4.237 x 3.525, or 14.936. The table below summarizes the relativities based on the one-way method.

Age Group		Car Size		
		Large	Medium	Small
Level	**Relativity**	1.000	1.725	4.237
1	1.000	1.000	1.725	4.237
2	3.525	3.525	6.082	14.936

We can see that this method fails to make the relativities as steep as necessary to reflect the combined increased risk from both variables. For example, the S2 car would be charged a premium of $1,493.60 instead of the $2,530 premium indicated by the data. Because this simple method uses the data to derive the relativity for each class variable independently of the other class variables, it produces results which are inconsistent with the data.

This effect is not due to a quirky example. There are very strong practical reasons that would lead us to reject one-way analysis. Normally, we would expect to see some degree of association between rating factors. An insurer's portfolio of risks is unlikely to be a random sample from the entire population of insurance risks - the insurer's pricing structure may target specific segments of the market and so we would expect to see this reflected in the relative loss-costs. We therefore prefer modeling techniques that can deal with these exposure-related issues directly.

This paper discusses some methods that can be used to calculate classification relativities and reduce the error that would otherwise occur by using one-way analysis. Section 2 will discuss the problem of risk classification analysis from a mathematical and statistical viewpoint and show some of the implied solutions from these approaches. This exposition revisits the work pioneered in the USA by Bailey [2], Bailey and Simon [3], and Brown [4], which are the foundations of American casualty practice in the area of classification ratemaking. We will then introduce another technique based on Generalized Linear Modeling (GLM) in Section 3 and discuss the advantages of implementing this technique. For those who have a strong background in classification ratemaking and GLM, we recommend skipping to Sections 4 and 5, where we present an application of this technique to credit insurance and discuss the results.

Section 2. Mathematical Formulation of Solution

2.1 Class Plan Objective - Minimum Bias Approach

To better understand the techniques being introduced, it will be useful to discuss the objectives of classification ratemaking and frame them in a mathematical context.

The objective of a classification plan is to replicate the actual loss cost relativities as closely as possible. Let's call the selected relativities x_i, y_j for the i^{th}, j^{th}, (etc.) values of the respective rating variables.[2] Let's call r_{ij} the actual loss cost relativity for the set of exposures that have both of these variable values (for example - youthful driver and large car). The goal is then, for all i, j, to have x_iy_j be as close to r_{ij} as possible (if we are designing an additive class plan, replace x_iy_j with $1 + x_i + y_j$), where "close" is measured by some bias function $f(r_{ij},x_i,y_j)$.

2.2 Example - Least Squares

For example, suppose we define a bias function as the weighted squared error:

$SSE = \Sigma_i \Sigma_j n_{ij} (r_{ij} - x_iy_j)^2$ where n_{ij} is the number of exposures in the ij^{th} cell.[3]

2 While we are dealing with two variables in this example, we can generalize to n variables. Similarly, we can generalize to allow for interactions. If we know that two variables interact (e.g., age and sex) then we can create a new composite variable formed for each combination of the categories of the original variables.

3 n_{ij} is used as a weight to reflect the relative exposure amount of the ij^{th} cell.

In minimizing SSE, we set $\partial SSE/\partial x_k = 0$, and solve for x_k in terms of y_j.

$$-2\sum_j y_j n_{kj}\left(r_{kj} - x_k y_j\right) = 0$$

$$\sum_j y_j n_{kj} r_{kj} = x_k \sum_j n_{kj} y_j^2$$

$$x_i = \frac{\sum_j n_{ij} r_{ij} y_j}{\sum_j n_{ij} y_j^2} \quad \text{and similarly}^4 \quad y_j = \frac{\sum_i n_{ij} r_{ij} x_i}{\sum_i n_{ij} x_i^2}$$

We will call this the least squares multiplicative model. For this model, the solution of the partial derivative equations leads to forms which can be solved iteratively. This approach proceeds by selecting initial values for each y_j and then using the model solutions to solve for each of the x_i's. The x_i's are then substituted into the equations for the y_j's to produce the next estimate of the y_j's. The process is repeated until the solutions at each iteration converge.

The indicated class relatives for the auto example, using the least squares multiplicative model, are as follows:

Age Group		**Car Size**		
		Large	**Medium**	**Small**
Level	**Relativity**	1.000	3.021	5.533
1	1.000	1.000	3.021	5.533
2	3.541	3.541	10.697	19.592

4 For the final x_i solution, the previous subscript of k is simply replaced with i to enable us to continue with the notation.

A detailed example of the iterative calculations is presented in Section 2.4 for the Poisson maximum likelihood multiplicative model.

The loss cost relativity, r_{ij}, is the loss cost for the ijth class divided by the loss cost for the base class, or by the total loss cost if there is no base class. For purposes of this paper, we will assume that there is a base class, unless specifically noted. The loss cost relativity can also be derived as the frequency relativity multiplied by the severity relativity. If each class has the same average claim size, then the severity relativity is unity for every class. In this case, the loss cost relativity r_{ij} is equal to the frequency relativity. The example in Section 1 assumes the same average claim size by class.

Allowing the subscript B to represent the base class, we can formalize this discussion as:

$$r_{ij} = \frac{L_{ij} / n_{ij}}{L_B / n_B} = \frac{s_{ij} m_{ij} / n_{ij}}{s_B m_B / n_B}$$

Where L_{ij} is the total loss in the ijth class, s_{ij} is the average claim in the ijth class, and m_{ij} is the number of claims in the ijth class.

If the classes have the same average claim size, i.e. s_{ij} equals s for all $_{ij}$, then:

$$r_{ij} = \frac{s m_{ij} / n_{ij}}{s m_B / n_B} = \frac{f_{ij}}{f_B}$$

which equals the frequency relativity. Here, f_{ij} is the frequency of the ijth class.

2.3 Class Plan Objective - Maximum Likelihood Approach

An alternate approach centers on answering the question "which x_i, y_j's are those that maximize the likelihood of the actual r_{ij}'s being generated?" This approach attempts to obtain the objective of the class plan via a firmer statistical setting, rather than minimizing a general subjective bias function. There are, of course, several items that could be considered random variables. For example, the class losses, L_{ij}, class claim counts m_{ij}, class severity s_{ij}, and class loss cost relativity r_{ij} can each be viewed as having underlying statistical distributions in which the x_i's and y_j's are parameters. In fact, the random variables could be placed at an individual exposure level, rather than a cell level.

If the random variable is r_{ij} at the individual class level and is drawn from the probability distribution g, then the likelihood function L, which is the product of the probabilities of independent observations, is $L = \prod_{i,j} g(r_{ij}; x_i, y_j)$ with the parameters x_i and y_j.

We can maximize the likelihood function by maximizing its logarithm, so

$$\ell n(L) = \sum_i \sum_j n_{ij} \ell n\left[g(r_{ij}; x_i, y_i)\right]$$

which we maximize by calculating the partial derivatives and setting them equal to zero.

2.4 Example - Possion Frequency

Let's work through the maximum likelihood estimate for a multiplicative model, $r_{ij} = x_i y_j$. For this model, we will assume that the random variable is the number of claims per class, m_{ij}, and that each class has the same severity. The Poisson density would be:

$$g(m_{ij}, x_i, y_j) = \exp(-h(x_i, y_j))h(x_i, y_j)^{m_{ij}} / m_{ij}!$$

Here, $h(x_i y_j)$ takes the role of the familiar lamda parameter. The parameter is a function of x_i and y_j. In the multiplicative model, $h(x_i, y_j) = x_i y_j f_B n_{ij}$ where f_B is the observed frequency of the base class. Because of the additive property of the Poisson distribution, this model will also result if the random variable is the number of claims per exposure and the lambda function equals $x_i y_j f_B$.

Either way, the likelihood function is:

$$L = \prod_{i,j} \frac{e^{-x_i y_j f_B n_{ij}} \left(x_i y_j f_B n_{ij}\right)^{m_{ij}}}{m_{ij}!}$$

$$\ell n(L) = \sum_{i,j}\left[-x_i y_j f_B n_{ij} + m_{ij} \ell n\left(x_i y_j f_B n_{ij}\right) - \ell n\left(m_{ij}!\right)\right]$$

$$\frac{\partial \ell n(L)}{\partial x_k} = \sum_j \left[-y_j f_B n_{kj} + m_{kj} / x_k\right] = 0$$

$$f_B \sum_j y_j n_{kj} = \frac{1}{x_k} \sum_j m_{kj}$$

(replacing k with i)

$$x_i = \frac{\sum_j m_{ij}}{f_B \sum_j y_j n_{ij}} = \frac{\sum_j \frac{m_{ij}}{f_{ij}} \frac{f_{ij}}{f_B}}{\sum_j y_j n_{ij}}$$

$$x_i = \frac{\sum_j n_{ij} r_{ij}}{\sum_j n_{ij} y_j}$$

which we will call the Poisson (multiplicative) model

Let's illustrate the use of the Poisson model by applying it to the previously introduced example. x_i will be car size, y_j will be age group, n_{ij} will be the number of exposures, and r_{ij} will be the actual claim frequency relativity. The first iteration of calculation[5] would be:

$x_1 = (n_{11}\, r_{11} + n_{12}\, r_{12})/(\, n_{11}\, y_1 + n_{12}\, y_2)$ Assume $y_1 = 1$, $y_2 = 4$, initially.

$= (100 * 1.0 + 300 * 4.7)/(\, 100 * 1 + 300 * 4)$

$= 1500 / 1300$

$= 1.15$

$x_2 = (n_{21}\, r_{21} + n_{22}\, r_{22})/(\, n_{21}\, y_1 + n_{22}\, y_2)$

$= (1200 * 3.1 + 500 * 14.6)/(\, 1300 * 1 + 500 * 4)$

$= 11000 / 3200$

$= 3.44$

$x_3 = (n_{31}\, r_{31} + n_{32}\, r_{32})/(\, n_{31}\, y_1 + n_{32}\, y_2)$

$= (500 * 8.4 + 400 * 25.3)/(\, 500 * 1 + 400 * 4)$

$= 14300 / 2100$

$= 6.81$

$y_1 = (n_{11}\, r_{11} + n_{21}\, r_{21} + n_{31}\, r_{31})/(\, n_{11}\, x_1 + n_{21}\, x_2 + n_{31}\, x_3)$

$= (100*1.0 + 1200*3.1 + 500*8.4)/(100*1.15 + 1200*3.44 + 500*6.81)$

$= 8000 / 7645$

$= 1.05$

$y_2 = (n_{12}\, r_{12} + n_{22}\, r_{22} + n_{32}\, r_{32})/(\, n_{12}\, x_1 + n_{22}\, x_2 + n_{32}\, x_3)$

$= (300*4.7 + 500*14.6 + 400*25.3)/(300*1.15 + 500*3.44 + 400*6.81)$

$= 18800 / 4789$

$= 3.93$

5 While the steps are displayed with r_{ij}, x_i, and y_j rounded, the exact figures are used in each step of the calculations.

After the first iteration, we would use the new y_j's to recalculate the x_i's and so on, until the results converged. The subsequent iterations are shown in the table below:

Parameter	First Iteration	Second Iteration	Converged Solution	Rebased Relativities
x_1 - Large Car Size	1.15	1.17	1.1703	1.000
x_2 - Medium Car Size	3.44	3.42	3.4169	2.920
x_3 - Small Car Size	6.81	6.83	6.8312	5.837
y_1 - Age Group 1	1.05	1.05	1.0481	1.000
y_2 - Age Group 2	3.93	3.92	3.9232	3.743

The rebased relativity for a specific class level is the converged solution divided by the base class level converged solution. For example the 2.920 relativity for the medium car size equals 3.417/1.170.

The resulting implied class relativities are as follows:

Age Group		Car Size		
		Large	Medium	Small
Level	Relativity	1.000	2.920	5.837
1	1.000	1.000	2.920	5.837
2	3.743	3.743	10.929	21.850

which is a significant improvement over the one-way relativity calculations. The improvement lies in the fact that the fitted class relativities for the Poisson model more "closely match" the relativities, r_{ij}, in the data.

2.5 Loss Ratio Relativities

Before proceeding, it is worth digressing to discuss the meaning of "actual losses." In standard ratemaking procedures, it is common to use loss ratios, rather than pure premiums, in a relativity analysis. However, loss ratios only give the required *change* in relativity, as the existing relativities are embedded in the denominator. Therefore, one must adjust the loss ratios to remove the effect of the existing relativities of any rating variables being analyzed in the study. This adjustment can be handled via the following steps:

1. Calculate a matrix of existing differentials, D_{ij}, where for a multiplicative model D_{ij} is the product of the current rate relativities for row i and column j. In the additive model, D_{ij} = 1 + the sum of the current rate relativities for row i and column j. The base class should have D_{ij} equal to 1.
2. Calculate the matrix of loss ratios, LR_{ij}.
3. Divide all of the loss ratios by the loss ratio for the base class. This will give "raw loss ratio relativities," W_{ij}.
4. Multiply each of the W_{ij}'s by D_{ij} to get the adjusted loss cost relativities, r_{ij}.

   This adjustment avoids double-correcting for the variables in the model.

Bailey [2], Bailey and Simon [3], and Brown [4] introduce a number of other models. In the Appendix to this paper, we will derive some of these additional models as well as show the solution to the above example (but not the calculations) for each of these models. While this set of models is not exhaustive, it gives the reader an indication of how to construct maximum likelihood estimates given an underlying distributional assumption, as well as other types of constraints. Finally, it should be kept in mind that by using alternative notations, a single model may often be written in several different forms and may arise through the optimization of different criteria.

Section 3. Introduction to GLMs

3.1 Introduction

This section provides a brief introduction to Generalized Linear Models (GLMs). Those who are familiar with this theory may wish to skip ahead to Section 4, which contains an application of GLMs for classification data. Several good introductory texts include those by Aitkin [5] et al and the SAS* Institute Inc.[1] The standard, complete reference is by McCullagh and Nelder [6].

3.2 Traditional Linear Models

Traditional linear models include the familiar simple and multiple regressions and Analysis of Variance (ANOVA) models, among others. GLMs include all of these linear models and extend well beyond the traditional frameworks by broadening most of the major assumptions. This implies that the use of multiple regression for classification ratemaking is a specific, albeit simpler, application of GLM.

Before proceeding to the general GLM framework, we will briefly recap the traditional linear model in matrix form:

$\bar{y} = X\bar{\beta} + \bar{\varepsilon}$ where

$\bar{y}$ is the nx1 vector of actual observed values;

X is the nxp matrix of explanatory variables;

$\bar{\beta}$ is the px1 vector of unknown parameters; and

$\bar{\varepsilon}$ representing the 'error' term, is the nx1 vector of independent, identically distributed (iid) normal random variables, with common variance, σ^2.

Note that a single observation, y_i, is modeled as $y_i = \vec{x}_i{}^T\vec{\beta} + \varepsilon_i$, where x_i is the i[th] row of the matrix X and $'$ is the matrix transpose operator. In the classification setting, the parameter vector, $\vec{\beta}$, contains parameters for all of the classification variables. The i[th] row of the matrix X would represent the actual risk characteristics of the i[th] insured .

Analysis generally proceeds by estimating $\vec{\beta}$ via least squares, which is equivalent to maximum likelihood estimation for these models. Confidence intervals, point estimates, and hypothesis tests can all be conducted using the estimated parameters, $\hat{\beta}$.

The assumptions are reviewed by analyzing the residuals, e_i, where

$$e_i = y_i - \hat{y}_i \; and \; \hat{y}_i = \vec{x}_i{}' \hat{\beta}.$$

A very thorough reference for the theory underlying linear models is by Searle [7]. Residual diagnostics is covered in Belsley et. al. [8].

Shortcomings of Traditional Linear Modeling

As GLM's encompass traditional linear models, GLM theory, model structure, and model diagnostics all have their impetus in the traditional models. One can view GLM theory positively as an extension of traditional linear model theory in which the traditional model assumptions are relaxed to include more real-life problems. Specifically, situations that GLM's can handle but traditional models cannot, without resulting to painful transformations, are:

1. Non-normal response variables (y) - for example, there is no reason to believe that claim count data which is discrete and non-negative can be modeled appropriately by a continuous distribution which includes negative values in its range.

2. Non-linear Structure. The traditional model is $\hat{y}_i = E[y_i|\bar{x}_i] = \bar{x}_i^T\hat{\beta}$ which is linear in $\hat{\beta}$. Note that this implies that there exists some $\bar{x}_i$ for which $\hat{y}_i$ is negative. If, again, the data is count data or loss data, the mean will usually not be negative.

3. Non-constant variance. Traditional linear models assume that the variance is the same for each class. However, the variance often fluctuates with the overall magnitude of the class mean. For example, in the Poisson case, the mean equals the variance. There is nothing constant about it.

3.4 GLM

The general discussion in this section will use the traditional notation of y for the response variable and x for the covariate vector. The x_i and y_j from Section 2 will appear in this section as well. However, in the latter occurrences, Section 2 will usually be referenced and hopefully the context of the discussion will remove any confusion as to which x and y are being referenced.

GLM theory is built for probability distributions from the exponential families of the form:

$$f(y) = \exp\left(\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right)$$

where θ are the underlying parameters, whose value may vary by class, and ϕ represents a scale parameter.

Exponential families include the normal, Poisson, gamma, and binomial distributions. The mean and variance of the exponential family are:

$$E[Y] = b'(\theta), \text{ which we denote } \mu,$$
$$Var[Y] = b''(\theta)\phi/W = V(\mu)\phi/W$$

where $'$ and $''$ denote first and second derivatives with respect to θ, $V(\mu)$ is a one-to-one variance function relating the mean and the variance, and W is the weight assigned to each observation. The weight is embedded in $a(\phi)$ and $c(y,\phi)$.

Two additional items that tend to arise are the link[6] and offset functions. The link function is a one-to-one function of the mean, g, such that $g(\mu_i)$ is modeled as $\vec{x}_i'\vec{\beta}$. Hence, a function of the mean, and not the mean itself, is modeled in a linear fashion. The offset function is generally used with the Poisson distribution to account for the level of exposure in each class.

6 In this paper, we will use only canonical link functions. Canonical links result in the linear predictor, $\vec{x}'\vec{\beta}$, equaling the natural exponential parameter θ.

For example, in the Poisson distribution: $f(y) = e^{-\lambda}\lambda^y/y! = \exp(y\log\lambda - \lambda)/y!$

and using the log link, $\theta = Log\mu = Log\lambda = \vec{x}'\vec{\beta}$

$$\begin{aligned}
&f(y) = \exp\left(y\theta - e^{\theta}\right)/y! \\
&b(\theta) = e^{\theta} \\
&b'(\theta) = e^{\theta} = \lambda = \mu = \mathrm{E}[\mathrm{Y}] \\
&b''(\theta) = e^{\theta} = \lambda = \mu = Var[\mathrm{Y}] = V(\mu) \\
&\phi = 1 \;\; and \;\; w = 1.
\end{aligned}$$

The fitted parameters, $\hat{\beta}$, are obtained as in the traditional models, via maximum likelihood estimation. However, a closed form solution for the estimates does not usually exist, so an iterative process is used to obtain the estimates.

Typically, for count data, for each class, the exposure, n_i, and number of claims y, might be available. The Poisson model would become: $f(y_i) = e^{-\lambda_i n_i}(\lambda_i n_i)^{y_i}/y_i!$

The log-likelihood contribution of y_i is: $-\lambda_i n_i + y_i\log\lambda_i + y_i\log n_i$.

Further, $\mathrm{E}[\mathrm{Y}_i] = \lambda_i n_i$, which on the log scale becomes:

$$\log\mathrm{E}[\mathrm{Y}_i] = \log\mu_i = \log\lambda_i + \log n_i = \vec{x}_i\hat{\beta} + \log n_i.$$

The exposure, n_i, is usually handled via an offset. For the Poisson model, the offset is $log\ n_i$. Once the parameters are fit, the estimated means are obtained as $\mu_i = g^{-1}(\theta_i)$. In a Poisson model with two variables and an intercept, $_{ij} = \exp\left(\vec{x}'\vec{\beta}\right) = \exp\left(\text{Intercept} + \alpha_i + \delta_j\right)$

The x_i and y_j for a multiplicative Poisson model presented in Section Two could then be obtained as $x_i = e^{\alpha_i}/e^{\alpha_B}$ and $y_j = e^{\delta_j}/e^{\delta_B}$. The estimated mean can be thought of as the predicted or fitted value.

3.5 The Poisson Example Revisited

We now show how our previously introduced example would be handled with this method. The following SAS code generates the data set to be used for the analysis:

```
DATA insure;
INPUT n m car $ age;
lnoffset = LOG(n);
*exposure       counts   car size        age group;
*n      m       car      age;
CARDS;
500     42      small    1
1200    37      medium   1
100     1       large    1
400     101     small    2
500     73      medium   2
300     14      large    2
;
RUN;
```

So, for example, there are 500 small cars (exposures) in age group 1 and this class had 42 claims. The model could be written as $\log \lambda_{ij} = Intercept + \alpha_i + \delta_j$, where α_i is the fitted parameter for car size i and δ_j is the fitted parameter for age group j.

To fit the Poisson regression model in SAS, we use the GENMOD procedure in the SAS/STAT module. The SAS code for this analysis is:

```
PROC GENMOD DATA = insure;
    CLASS car age;
    MODEL m = car age /
        DIST = Poisson
        LINK = log
        OFFSET = lnoffset;
    RUN;
```

The parameter estimates along with their standard errors are displayed below:

Parameter	Estimate	Standard Error
Intercept	-1.3168	0.0903
Large car size	-1.7643	0.2724
Medium car size	-0.6928	0.1282
Small car size	0.0000	0.0000
Age Group 1	-1.3199	0.1359
Age Group 2	0.0000	0.0000

Like linear regression, the model can be fitted either with or without an intercept. The above model has assumed that the small car size for age group 2 is the base class. The base class will have log λ_{32} equal to the intercept. By taking the inverse link function, $g^{-1} = exp$, a table of fitted expected frequencies can be constructed:

$\lambda_{ij} = \exp\left(Intercept + \alpha_i + \delta_j\right)$			
	Car Size		
Age Group	**Large**	**Medium**	**Small**
1	.0123	.0358	.0716
2	.0459	.1340	.2680

Now if we wanted to use large cars and age group 1 as our base class for a rating plan, and if the severity for each class was the same, the class relativities could be obtained by dividing the previous table through by λ_{11}. On the other hand, multiplicative class factors could be obtained for each level within the variable as exp(level parameter - base level).

For example, if large cars for age group 1 are the base class, the medium car class relativity could be computed as exp(1.7643 - .6928) = 2.920. The resulting class relativities are displayed below:

Age Group		**Car Size**		
		Large	**Medium**	**Small**
Level	**Relativity**	1.000	2.920	5.837
1	1.000	1.000	2.920	5.837
2	3.743	3.743	10.929	21.850

More detailed examples of using GLM's in auto classification rate making in the United Kingdom are described in Reference 9.

3.6 Model Validation

We will discuss two types of goodness of fit or validation tests. First, we will introduce some more technical tests which do not usually get mentioned with traditional models. Then we will discuss some analogs of the more traditional residual plots and other less objective tests.

The "more technical" tests center on two statistics, which often have asymptotic chi-square distributions. The first statistic centers on an item known as the deviance. For a fixed ϕ, the scaled deviance is defined as:

$$D^*(\bar{y},\bar{\mu}) = 2(\ell nL(\bar{y},\bar{y}) - \ell nL(\bar{y},\bar{\mu}))$$

where $\log L$ is the log likelihood. This looks very much like the log of the likelihood ratio test statistic.

For the Poisson distribution (with weight one, as shown previously):

$$\ell nL(\bar{y},\bar{\mu}) = -\Sigma\mu_i + \Sigma y_i \ell n\mu_i - \Sigma \ell n(y_i!),$$
$$\ell nL(\bar{y},\bar{y}) = -\Sigma y_i + \Sigma y_i \ell n y_i - \Sigma \ell n(y_i!), \text{ and}$$
$$D^*(\bar{y},\bar{\mu}) = 2\Sigma[y_i \ell n(y_i/\mu_i) + (\mu_i - y_i)]$$

The second statistic used is Pearson's chi-square statistic $Q = \sum w_i (y_i - \mu_i)^2 / V(\mu_i)$

This statistic should also have a somewhat familiar look. In fact, y_i-μ_i is the residual, or actual less expected amount. The scaled Pearson chi-square statistic is Q/ϕ, which is Q in this Poisson case For the Poisson case, Q becomes the very familiar

$$\sum \frac{(Observed - Expected)^2}{Expected}$$

This form can be used to evaluate the types of models presented in Section 2.

Both of the scaled statistics have an asymptotic chi-square distribution under various general conditions. The degrees of freedom is equal to the number of observations less the number of estimated parameters.

The deviance lends itself readily to testing heirachical or nested model structures. For two given models, M1 and M2, where M2 contains all the predictors in M1 as well as some additional ones, then the difference of the deviances for Model 1 and Model 2 is equal to twice the difference in the log likelihoods under each model. Thus the deviance can be compared to the chi-square distribution to test the significance of adding the new variables, as noted in Hogg & Klugman [10]. The degrees of freedom for the statistic is equal to the number of new variables added.

As with traditional models, one may examine residual plots in an attempt to validate the model. Three simple types of plots may be used – quantile plots, burst plots, and predictor plots.

Quantile plots are used to check the underlying distributional assumption. The traditional analog is the normality plot of the residuals. As with the traditional plot, a theoretical quantile - observed quantile (Q-Q) plot that is linear supports the distributional assumption made.

Burst plots are used to test the randomness of the residuals. As in traditional models, the residuals are plotted against the fitted points. If the plot appears to be a random burst with no discernable pattern, then the model structure is supported.

Predictor plots are used to ensure that the variables used in the model have been properly reflected. In these plots, the residuals are plotted against each of the variables. A good model will not display any patterns in these plots. The presence of a pattern usually indicates some sort of bias in the fit and may point to a more complex breakdown of model assumptions. For example, in fitting models to claim severities, a common problem is increasing variability with increasing severity and would be reflected in these plots. This problem often leads to a situation of systematic under-prediction and over-prediction and can go unnoticed without these diagnostic procedures.

If there are points that prevent the plots from conforming to the above requirements (outliers), then corrective action is necessary. The most common course is to look at the specific data points concerned, exclude them from the data set (if they are relatively few in number), and refit the model. If there is a significant number of outliers, then this indicates a more serious problem, such as the one discussed above, and may indicate the need for reconsidering basic model assumptions.

It is very important to be aware of the model structure when reviewing the residual plots. Discrete data, or other model forms, may induce residual behavior which does not conform with the traditional expectations, but which is still acceptable. For example, consider a Bernoulli (binomial) model in which each observation is a claim (1), or not a claim (0), for each given exposure. Then the raw residual will either be 1-p or -p. This separation, which is not encountered in the traditional continuous normal models, leads to different expectations of what an acceptable burst or predictor plot would look like. For discrete data, it is often more useful to examine the ratios of fitted versus actual data, as we discuss next.

A practical model validation procedure is to examine tables of the ratios of fitted to actual (F:A) number of claims or total cost of claims. The aim of this analysis is to establish if there is any systematic bias in the model estimates. In general, for any subclass, we do not expect the F:A ratio to be 100%. It may be greater or lesser than 100% depending on what model constraints are in place. For example, claim severities below a set amount may be excluded for the reason of financial insignificance and hence the average claim cost will be higher. This would cause the fitted total claim cost to be higher and hence the F:A ratio to be greater than 100%. As long as the F:A ratio is reasonably consistent across all levels of the relativity factors, there is no cause for concern. However, if the F:A ratio declines as age of driver increases, for example, this would indicate a systematic bias in the model for age of driver.

Correcting systematic bias would require further investigation as to the source of the bias. It could be due to one or more variables being omitted from the final model or it may simply be due to small amounts of exposure at young ages. Another possible cause of this bias may be a changing book of business over time.

One final principle of practical model validation is "the eyeball axiom". By graphing the indicated relativities for each variable, one can examine these estimates (and their confidence intervals) for reasonableness. These graphs can be telling in terms of data quality as well as implied relationships.

7 Why use GLM?

The astute reader may have noticed that the maximum likelihood example in Section 2 and the GLM example produce the same relativities. As the GLM estimates are also based on maximum likelihood, the solutions should be the same. This leads to the obvious question "Why bother with GLM if I can iterate?"

There are several reasons to implement a model using GLM. There are a number of statistical software packages available which handle GLM. GLM and these software packages have the following advantages:

1) The software packages include a general fitting routine that is applicable to any GLM. Simple closed form iterative solutions may not be available for a specific GLM.
2) Continuous rating variables, such as actual age, can be incorporated into a model.
3) Most of the common model forms, such as poisson, binomial, normal, lognormal, and gamma, are already included as standard models. Non-standard exponential family

models can be included with a few lines of code. The package saves one the time of deriving, programming, and verifying iterative models.

4) The process of exploring residual plots, goodness of fit statistics, variable groupings, and variable interactions is easier.

5) Most packages produce "standard errors" for each parameter. These can also be used to evaluate the model.

6) Most of the packages are fairly efficient. For example, the model to be discussed in Section Four was fit to several hundred thousand records in a few minutes using SAS.

7) Finally, when viewed as an extension of traditional linear models, the whole GLM modeling process may seem more natural than an iterative formula, or at least less alien. This will certainly assist the actuary in relating the analysis to non-technical decision makers, who may be somewhat familiar with regression.

Section 4. Applications of GLMs

4.1 Introduction

GLM techniques are well established in rating for personal lines insurance in some areas of the world (auto and household). Typically, claim frequency and claim severity are modeled separately and the results combined to produce loss cost relativities. Claim frequency is often modeled using Poisson or negative binomial error structures, while claim severity is often modeled using gamma or log-normal error structures. Model structures are usually multiplicative, that is for a given cross-classification of risk-factors called the "base class," the product of the various loss cost relativities is unity. Relativities greater than one indicate increased risk while relativities less than one indicate reduced risk, relative to the base class. As mentioned in Section 1, a separate exercise is needed to establish the actual base premium for the base class.

The above description, although brief, summarizes the situation for many insurance applications. However there is ongoing debate on issues such as multiplicative versus additive model structures, whether frequency and severity should be modeled separately or jointly, the correct treatment of no-claim-bonus scales, etc. The interested reader should consult the literature for discussion of these and other issues [5], [9].

4.2 Credit Insurance

The example we present in this paper is based on analysis of a U.S. financial institution's claims experience. In particular, our aim in modeling terms is to improve their ability at the time of extending credit to correctly assess high- and low- risk applicants, using information collected at the time of loan application. By developing these models, the loan default performance of the outstanding balances should improve, increasing profitability.

A large amount of information is collected during the application process, including credit score, amount of the loan, type of collateral, income ratios, marital status, loan term, loan purpose, state, borrower age, gender, etc. Some of this information was not used because of insurance and lending nondiscrimination requirements.

Some of the information collected is naturally categorical in nature, such as type of collateral. Some of the information, like age of borrower, is naturally continuous. More generally, the categorical nature of many rating factors and the number of rating factors gives rise to the problem that there may be large number of cross-classified cells (classifications). However, the actual number of cells is usually much smaller and there is often a large number of cells with very small exposure.

4.3 GLM Model for Credit Insurance Claims

As a loan (single exposure) only has two possible outcomes - claim or no claim - we chose to model claim frequency using a multiplicative model with a binomial error structure, using a logit link function. This approach is identical to logistic regression. The regression model equation is:

$$Logit(P_i) = Log\left(\frac{P_i}{1-P_i}\right) = \bar{x}_i^T \bar{\beta}$$

where

- P_i is the probability that the i^{th} loan becomes a claim,
- $\bar{x}_i^T$ is the vector of risk factors for the i^{th} loan, and
- $\bar{\beta}$ is the vector of risk factor relativities.

The model is fitted by maximum likelihood. For our work, we have used The SAS System, in particular PROC GENMOD from the SAS/STAT module.

In the context of multiplicative relativities, the need for an interaction model means that there are significant exposure-related differences for the particular factors in question. This is analogous to the assumption about equal underlying exposure breaking down for one-way analysis. In the GLM case, this can be corrected by fitting a model with terms like $x_j * x_k$ and excluding x_j and x_k. This is done even though testing for significance of the interaction effect would include all of the terms.

Our model includes only main effects. We did not model any conditional relationships between variables that would take into account interaction effects. During the model validation process, we did not see any sign of significant bias that suggested the need for these interaction terms.

4.4 Model Validation

As discussed in Section 3, the usual statistical tool for model validation is residual analysis. This approach confirms that the underlying distributional assumptions have not been violated, as well as ensures that there is no systematic bias in the parameter estimates. The first of these checks would often be conducted via two plots. The first is a quantile plot of residuals versus quantiles from the assumed error distribution. The second is a 'burst' plot of residuals versus actual values. Systematic bias would be explored with a series of plots of residuals versus the rating factors. Trends in the residuals would indicate a bias.

In the case of a binomial error structure with (0,1) outcomes, the residual plots as described above may not provide much added value. Due to the potential for many cells with small exposure, plots at a higher level of summarization may still not be much of an improvement. In this example, where the observed claim frequency is usually very low (generally less than 10%), these conditions are exacerbated.

We have relied upon examination of tables of actual versus expected scaled claim frequency to provide validation. Since we fit models to loans originated in one year and validated them against loans originated in the following two years, it was necessary to scale the expected number of claims for latter two years to equal the observed number of claims. Any systematic departure from actual-to-expected ratios of 100% is evidence of bias. The results of such validation for the loan data indicate that the models fitted were robust with no significant bias.

4.5 Rating Factors

The five rating factors used for the models presented here are:

Credit Score: Of the primary borrower, as assessed by an external credit rating agency. Credit scores range from about 400 to 800, with higher scores indicating a better rating. We grouped credit score into 10 bands (low-648, 649-677, 678-697, 698-714, 715-728, 729-742, 743-755, 756-768, 769-782, 783-high) selected to evenly divide the exposures. The base class band is 715-728. Credit scores are whole numbers.

Loan Amount: In thousands of U.S. dollars, banded into seven groups (low-50, 50-75, 75-100, 100-125, 125-150, 150-175, 175-high). The base class is 75-100. Actual loan amounts are in dollars. The groups are formed such that the 50-75 group includes loans of at least $50,000, but less than $75,000.

Financial Commitment Ratio: Loan commitments as a percentage of salary, banded into 8 groups (low-18, 18-20, 20-22, 22-24, 24-26, 26-28, 28-30, 30-high). The base class is 20-22. As above, 20-22 means a commitment of at least 20%, but less than 22%.

Loan Term: The length of the loan payment schedule, presented in months and split into two groups (0-5 years, 5+ years). The base class is 5+ years.

Loan Purpose: Whether the loan is for a new venture or to refinance an existing loan. The base class is refinance.

Multiplying out the number of categories of rating factors gives a potential 2,240 cells for this particular model and requires 25 parameter estimates. The base class loan is for a borrower who rates a credit score between 715 and 728, has borrowed between $75,000 and $100,000, has a financial commitment ratio of between 20% and 22%, a loan term of more than 5 years, and is refinancing an existing loan.

In general, the variable groupings proceeded along natural boundaries. Some of the groups were selected to produce class levels of equal width or exposure content. The base class was generally selected as the largest or most central class.

Section 5. Binomial GLM Model Results

5.1 Explanation of the Graphs

The graphs which follow are relativity plots from the binomial model fit. The relativities have had one subtracted from them. Therefore, positive relativities denote increased risk while negative relativities imply decreased risk relative to the base class. The right-pointing triangle indicates the relativity with the value displayed immediately to its right. The vertical bar to the left of the triangle indicates the uncertainty of the relativity estimate as measured by its standard deviation. In these plots, we have shown an 80% confidence interval, based on the asymptotic normality of the maximum likelihood estimates. In some cases, however, the extent of the confidence interval has been limited by placing an upper limit on the range displayed. The base class for each rating factor has a relativity of one, which appears in the graphs as zero with no error bar. The bars under each relativity indicate the level of exposure for each category of the rating variable.

To calculate the overall relativity for a given cross-classification, the relativities are multiplied together. For example for a borrower with a credit score in the band 698-714, a loan between $50,000 and $75,000, a financial commitment ratio between 26% and 28%, a loan term less than 5 years, refinancing an existing loan, has a risk relativity of 43% relative to the base class (0.43 = 1.42 x 0.77 x 1.71 x 0.23 x 1.00).

5.2 Discussion of Results

In this section, we present the raw results of the binomial GLM analysis. In deference to the proprietary nature of these underwriting and rating models, and for ease of presentation, we have treated the data in the following manner for this paper:

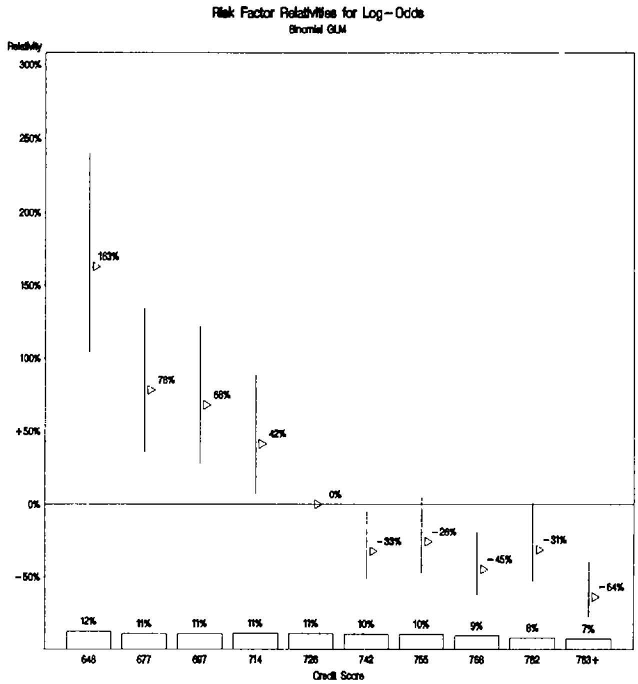
- We have transformed the underlying data so the numeric relationships shown in this paper are only illustrative;

- We have fitted a limited model of only five variables to the data, although there are additional explanatory variables; and

- We have treated the continuous variables as categorical, although it is statistically sub-optimal.

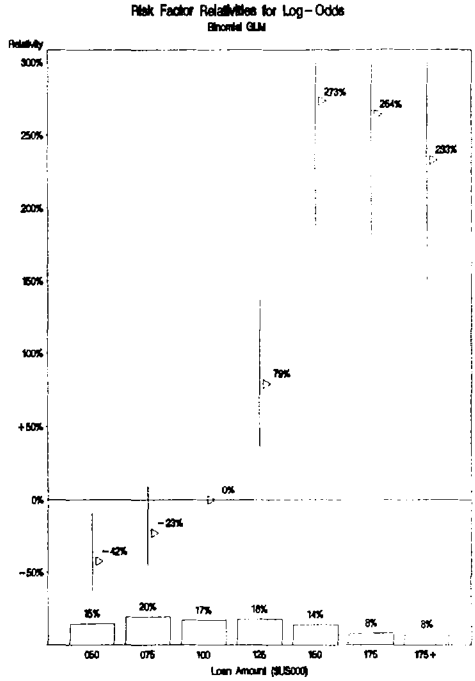
Given these treatments, no quantitative conclusions should be drawn from the examples shown herein.

5.2.1 Credit Score



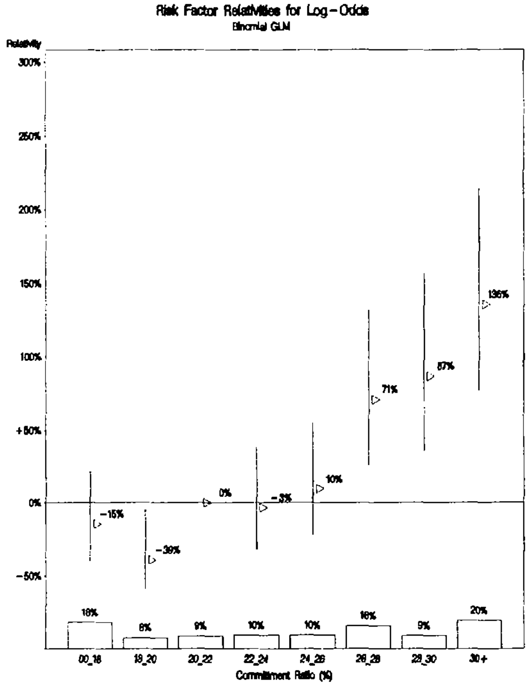
The shape of relativities for credit score is as expected, an almost monotonically decreasing function of credit score. In practice, it may be preferable to use credit score as a continuous variable (albeit transformed) and fit only one parameter instead of nine. A sensible transformation might be of the exponential or logistic form.

5.2.2 Loan Amount



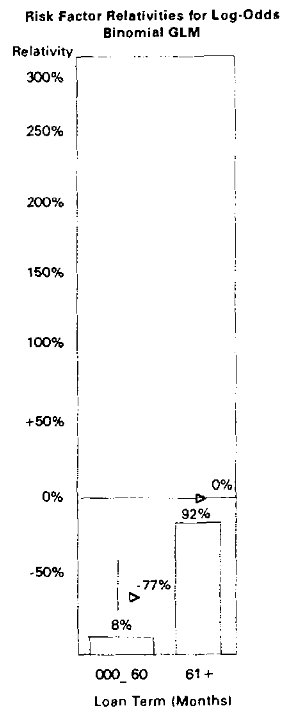
The results for loan amount behave generally as expected. We had thought that there would be a more gradual and monotonic pattern past $150,000. However, the error bars for the larger loan classes are particularly wide. It may well be that the apparent reduction in risk is a result of management action, such as increased underwriting for large loan values. If the indications between $150,000-200,000 were lower, loan amount could be fit as a continuous quantity, using a suitable transformation such as the hyperbolic tangent.

5.2.3 Commitment Ratio



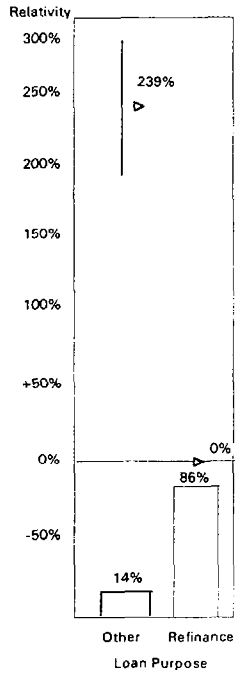
Again, the results for commitment ratio are largely in line with expectations, except perhaps for the apparent upturn for the lowest band. This hook may indicate that there is a base level of relative risk reduction. A hyperbolic tangent transformation may be appropriate for modeling this as a continuous variable. The transformation would also imply that at the upper end of the scale, there would be a limiting level of risk deterioration.

5.2.4 Loan Term



Loan terms of less than five years appear to be substantially less risky than loan terms greater than five years. This may be due to the quicker build-up of equity in the loan or more careful underwriting of shorter duration loans, which have lower profit potential.

5.2.5 Loan Purpose



Refinanced loans appear to be less risky than new ventures. This is likely due to the stable history required for a bank refinance, while new ventures may be more uncertain.

5.3 Smoothing Results

The graphs presented in Section 5.2 display the raw relativities that come from the model fitting process. In practice, adjustments may be required before implementing the model. The error bars, as well as the exposure measures give an indication of the reliability of the particular estimates and the potential for these adjustments. In the case of the continuous variables, the shape of the relativities gives an indication for possible functional forms to be used for refitting. In addition, a practical model must take account of the fact that manual management intervention may not be in place in the future (such as for loan-to-value) and hence the shape of the relativities may need to be altered to reflect this. Finally, expense and profit allocation issues, as well as marketing focus, must be considered.

Appendix - Additional Models and Examples

As we've mentioned in the paper, Bailey [2], Bailey and Simon [3], and Brown [4] have introduced a number of models in their studies. The Poisson Maximum Likelihood and Least Squares Multiplicative models of earlier sections were from Bailey and Brown, respectively. However, Bailey did not develop his model as a MLE for the Poisson distribution. He had developed this model by assuming "the balance principle," or that the average error for any given class should be zero.

Expressed mathematically: For all i,

$$\frac{\sum_j n_{ij}\left(r_{ij} - x_i y_j\right)}{\sum_j n_{ij} r_{ij}} = 0$$

$$\sum_j n_{ij} r_{ij} - \sum_j n_{ij} x_i y_j = 0$$

$$x_i = \frac{\sum_j n_{ij} r_{ij}}{\sum_j n_{ij} y_j}$$

which happens to be the Poisson model. The second line in the derivation above provides an additional interpretation of the balance principle. When viewing a fixed level of one of the row rating or column rating variables, we see that the total of the actual row (column), $\Sigma n_{ij}, r_{ij}$, must equal the total estimated by the rating factors, $\sum_j n_{ij} x_i y_j$ for a row,

or $\sum_i n_{ij} x_i y_j$ for a column.

Bailey also developed an additive model using the same constraint, which can be shown as:

$$\frac{\sum_j n_{ij}\left(r_{ij} - x_i - y_j - 1\right)}{\sum_j n_{ij} r_{ij}} = 0$$

$$\sum_j n_{ij}\left(r_{ij} - y_j - 1\right) - x_i \sum_j n_{ij} = 0$$

$$x_i = \frac{\sum_j n_{ij}\left(r_{ij} - y_j - 1\right)}{\sum_j n_{ij}}$$

which is <u>not</u> the MLE for an additive Poisson model.

We have chosen to present the additive model in a slightly different format than Bailey and Brown. Brown presents the "base rate" as $BR_a + x_i + y_j$ and $BR_m x_i y_j$ for the additive and multiplicative model, respectively. We have chosen to present these forms as, $BR\left(1 + x_i + y_j\right)$ and $BRx_i y_j$, respectively. The change in the additive form makes the discussion easier to follow because:

1) The loss cost relativity, r_{ij}, is on the same scale for either model. For example, a class that is 25% worse than the base class will have a relativity of 1.25, regardless of the model format. The scale in Bailey and Brown's interpretation is not so clear for the additive model. For example $r_{ij} = x_i + y_j$ could equal $75.00.

2) The same scale certainly makes the loss cost -vs- loss ratio discussion in Section 2 more easily understood.

In Bailey and Simon, a second multiplicative model was derived which minimizes the Chi-Squared value, rather than adhering to the balance principle. The Chi-Squared statistic is equal to:

$$Q = c \sum_i \sum_j \frac{n_{ij}\left(r_{ij} - x_i y_j\right)^2}{x_i y_j}$$

To minimize this, we set the partial derivatives equal to zero: $\dfrac{\partial Q}{\partial x_k} = 0$.

$$\sum_j \frac{-2y_j^2 x_k n_{kj}\left(r_{kj} - x_k y_j\right) - n_{kj} y_j \left(r_{kj} - x_k y_j\right)^2}{x_k^2 y_j^2} = 0$$

$$\sum_j 2x_k n_{kj}\left(r_{kj} - x_k y_j\right) + \frac{n_{kj}}{y_j}\left(r_{kj}^2 - 2x_k y_j r_{kj} + x_k^2 y_j^2\right) = 0$$

$$\sum_j 2x_k n_{kj} r_{kj} - 2x_k^2 n_{kj} y_j + \frac{n_{kj} r_{kj}^2}{y_j} - 2x_k n_{kj} r_{kj} + n_{kj} x_k^2 y_j = 0$$

$$\sum_j \frac{n_{kj} r_{kj}^2}{y_j} - x_k^2 n_{kj} y_j = 0$$

$$\Rightarrow \quad x_k^2 \sum_j n_{kj} y_j = \sum_j \frac{n_{kj} r_{kj}^2}{y_j}$$

$$\Rightarrow \quad x_k = \sqrt{\sum_j \frac{n_{kj} r_{kj}^2}{y_j} \Big/ \sum_j n_{kj} y_j}$$

Brown chose to approach the classification problem from the statistical standpoint. If the losses for ij[th] cell (class) L_{ij} *equals* $n_{ij}\, r_{ij}\, P_B$, where P_B is the pure premium for the base class, then $E\left(L_{ij}\right) = n_{ij} p_B E\left(r_{ij}\right)$

$= n_{ij} p_B x_i y_j$ (or $n_{ij}\, P_B\, (x_i + y_j + 1)$ for an additive model).

Suppose we assume the losses in each cell to be distributed exponentially with parameter θ_{ij}, then $E\left(L_{ij}\right) = \theta_{ij}, f\left(L_{ij}\right) = \dfrac{1}{\theta_{ij}} e^{-L_{ij}/\theta_{ij}}$ *and* $n_{ij} p_B x_i y_j = \theta_{ij}$, so

$$f(L_{ij}) = \frac{1}{n_{ij} p_B x_i y_j} e^{-(n_{ij} r_{ij} p_B / n_{ij} p_B x_i y_j)}$$

$$= \frac{1}{n_{ij} p_B x_i y_j} e^{-(r_{ij}/x_i y_j)}$$

The likelihood function

$$L = \prod_{i,j} f(L_{ij})$$

$$= \prod_{i,j} \frac{1}{n_{ij} p_B x_i y_j} e^{-(r_{ij}/x_i y_j)}$$

$$\ell n L = \sum_i \sum_j \ell n\left(\frac{1}{n_{ij} p_B x_i y_j}\right) + \ell n\left(e^{-r_{ij}/x_i y_j}\right)$$

$$= -\sum_i \sum_j \ell n(n_{ij}) + \ell n(p_B) + \ell n(x_i) + \ell n(y_j) + (r_{ij}/x_i\, y_j)$$

$$\frac{\partial\, \ell n L}{\partial x_k} = -\sum_j \left(\frac{1}{x_k} + \frac{r_{kj}}{x_k^2 y_j}\right) = 0$$

$$\Rightarrow \quad \frac{1}{x_k} \sum_j 1 = \frac{1}{x_k^2} \sum_j r_{ij} / y_j$$

$$x_k = \frac{\sum_j r_{ij} / y_j}{\sum_j 1}$$

This approach can be used for additive models and with different distributions. For example, assume

$$
\begin{aligned}
& L_{ij} \sim N\left(\mu_{ij}, \sigma_{ij}^2\right) \\
& \mu_{ij} = n_{ij} p_B \left(x_i + y_j + 1\right) \\
& \sigma_{ij}^2 = n_{ij}\sigma^2 \ (\textit{see footnote } 7) \\
& f\left(L_{ij}\right) = \frac{1}{\sigma_{ij}\sqrt{2\pi}} e^{-\left[\frac{1}{2\sigma_{ij}^2}\left(L_{ij}-\mu_{ij}\right)^2\right]} \\
& = \frac{1}{\sigma\sqrt{2\pi\, n_{ij}}} e^{-\left[\frac{1}{2n_{ij}\sigma^2}\left(r_{ij}n_{ij}p_B - n_{ij}p_B\left(x_i+y_j+1\right)^2\right)\right]} \\
& = \frac{1}{\sigma\sqrt{2\pi\, n_{ij}}} e^{-\frac{p_B^2 n_{ij}}{2\sigma^2}\left(r_{ij}-x_i-y_j-1\right)^2} \\
\Rightarrow \quad & \ell nL = \sum_i \sum_j - \ell n\left(\sigma\sqrt{2\pi/n_{ij}}\right) - p_B^2 \sum_i \sum_j n_{ij}\left(r_{ij} - x_i - y_j - 1\right)^2 / 2\sigma^2 \\
& \frac{\partial\, \ell nL}{\partial x_k} = \frac{p_B^2}{2\sigma^2} \sum_j 2n_{kj}\left(r_{kj} - x_i - y_j - 1\right) = 0 \\
& \sum_j n_{kj}\left(r_{kj} - y_j - 1\right) = x_k \sum_j n_{kj} \\
& x_k = \sum_j n_{kj}\left(r_{kj} - y_j - 1\right) \Big/ \sum_j n_{kj}
\end{aligned}
$$

which is the same as the Bailey [2] additive model. This solution can also be used for a multiplicative lognormal model by taking the logarithm of the data.

These are obviously just samples of many possible models involving different distributional assumptions. For a three (or more) variable model, one could use a mixed additive-multiplicative model, where $r_{ijk} = x_i y_j + z_k$. This would be solved using the same process.

---

7 This form essentially assumes that each exposure is independent and distributed $N(P_B(x_i + y_j + 1), \sigma^2)$. As the sum of normal random variables is normal, the distribution of the cell losses, L_{ij}, follows.

In concluding this appendix, we thought it might assist the reader in working with the models shown if we gave the values of the class plan, for the two variable example in the paper, solved using each of the models discussed.

First Iteration

	Bailey Additive	Bailey-Simon Multiplicative	Exponential Multiplicative
X_1	0.500	1.155	1.083
X_2	4.588	3.448	3.367
X_3	13.556	6.867	7.356
Y_1	-3.408	1.054	.994
Y_2	8.111	3.911	4.026
Initial Y_1, Y_2	(0, 3)	(1, 4)	(1, 4)

Second Iteration

	Bailey Additive	Bailey-Simon Multiplicative	Exponential Multiplicative
X_1	-2.482	1.175	1.083
X_2	5.490	3.439	3.365
X_3	13.177	6.870	7.363
Y_1	-3.738	1.054	.994
Y_2	8.607	3.910	4.026

Converged Solution

	Bailey Additive	Bailey-Simon Multiplicative	Exponential Multiplicative
X_1	-2.802	1.175	1.083
X_2	5.587	3.439	3.365
X_3	13.136	6.870	7.363
Y_1	-3.774	1.054	.994
Y_2	8.660	3.910	4.026

The Bailey additive model appears to be much more sensitive than the other two models to the choice of initial values. In fact, the implied rate for the base class is negative. This result occurs in part because L1 is the smallest class in terms of exposures and has the lowest frequency. The failure of the simple additive model to reflect interactions contributes to the dilemma as well. These observations, coupled with the balance principle, result in a nonsensical model. Using another base class or Bailey's original model, as previously noted, continues to produce the unreasonable result. If there were more levels for each class, the model could also be constrained to have x_I and y_J equal zero, but the iterative formulas would change. This entire problem is one argument in favor of multiplicative models rather than additive models.

These relativities can be multiplied (or added) together, and compared to the actual relativities using validation techniques discussed in the paper. In the example, for the largest class, M1, the various model relativities are displayed in the table below.

M1 Class Relativities

Method	Relativity
Actual Data (r_{ij})	3.083
One-Way Method	1.725
Bailey - Simon Multiplicative	2.926
Exponential Multiplicative	3.108
Poisson MLE (Bailey Multiplicative)	2.920

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Evaluation of the Qualified Loss Management Program for Massachusetts Workers' Compensation

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Background

The Massachusetts Qualified Loss Management Program (QLMP), which became effective November 1, 1990, is intended to provide incentive to workers' compensation insureds to seek the assistance of professionals to reduce their workplace losses. A prospective credit is applied to the premium of an assigned risk insured who subscribes to a qualified loss management program. The credit is given for a period of up to four policy years, provided the insured remains in the Program for a corresponding period of time. Credits are halved in the third year and quartered in the fourth year, since insureds will be able to realize premium savings through the application of the experience rating plan as their reduced losses become reflected in their experience rating modification factors.[1]

The Program is available to any insured in the Assigned Risk Pool and to credit-eligible insureds who are taken out of the Pool into a voluntary market guaranteed cost plan while remaining in the Program. Table 1 displays the participation in the program. It should be noted that many insureds have taken some or all of the same loss management steps, but were not

[1] The Appendix to this paper provides a fuller description of the QLMP. In particular, the complete schedule of credits is displayed. This schedule has been in effect since January 1, 1993.

eligible for a QLMP credit. For example, if an employer in the voluntary market signed up for the same program with the same loss management firm, they would not be eligible for an official QLMP credit.[2]

Credits for individual approved loss management firms are determined primarily by the loss reduction success experienced by all of the subscribing employers of the firm for the past seven years. Table 2 displays an example of such a calculation. The maximum possible credit is now 15%, increased from an original maximum credit 10%. This increase in the maximum credit was warranted based on the excellent overall results as evidenced by this evaluation.

Evaluation of the Program

An evaluation of the results achieved by the Qualified Loss Management Program was performed in November, 1995. The impact of the Program as a whole can be seen by comparing the aggregate loss ratio[3] improvement experienced by the participants in the QLMP dataset from the year prior to participation in the Program to Year 1, Year 2, or Year 3 in the Program with the improvement over the same time period seen in the aggregate data from all other risks not in the QLMP.

Numerous loss ratio comparisons were made in order to discern all effects that the Program might have on insureds:

- Since the Massachusetts workers' compensation environment was changing so dramatically over the period studied (September 1990 to August 1993), separate comparisons were made for the three 12-month periods for clarity.

[2] However, there is nothing preventing insurers from applying their voluntary market pricing tools in this situation.

[3] For each insured, the loss ratio is for a policy. Aggregated the data covers various different policy periods.

- Loss ratios were compared at first, second, and third report (where available) to determine whether the improvement seen at first report continues as losses mature.
- Separate comparisons were made for first-year, second-year, and third-year participants to see whether the salutary effects would continue, strengthen, or weaken with continued participation in the Program.
- Loss development from first to second or third report was compared for participants vs. other insureds to see whether the QLMP provider's case management or return-to-work programs might temper the deterioration typically seen in loss ratios.
- For further refinement, the analysis of loss ratio improvement was broken down by premium size groupings and experience modification groupings.

Summary of Main Results of the Evaluation

- As summarized in Table 3, the analysis indicates an improvement in loss ratios for insureds participating in the QLMP of over 30% on average.
- The QLMP participants started with a substantially higher aggregate loss ratio than the market as a whole, but during their first year of participation the gap narrowed significantly.
- The difference in loss ratio improvement experienced by participants as compared to nonparticipants actually *increased* at second report and remained significant at third report.
- Participants receiving second-year credits showed significantly better loss ratio improvement in Year 2 as well as in Year 1 when compared to the total market.

Overall, the Program is producing a beneficial effect on the loss experience of participating insureds, by concentrating efforts on loss control and prevention, as well as post-injury response and return-to-work programs.

<u>**Details of the Results of the Evaluation**</u>

Exhibit 1 depicts the effect on loss ratios of the Program over the entire policy period of September 1990 to August 1993. The QLMP participants started with a substantially higher aggregate loss ratio than the market as a whole, but during their first year of participation the gap narrowed significantly.

Exhibit 2 displays loss ratios at both first report and second report, comparing QLMP participants to nonparticipating Assigned Risks. One of the most important concerns about the Program is whether the improvement seen at first report will continue as losses mature; in this exhibit the difference in loss ratio improvement experienced by participants as compared to nonparticipants actually *increased* at second report and remained significant at third report. Future Program evaluations will continue to monitor results at later maturities.

Exhibit 3 shows two effects of second-year QLMP participation. First, participants receiving second-year credits showed significantly better loss ratio improvement in Year 2 as well as in Year 1 when compared to the total market. In fact, the aggregate loss ratio for second-year participants was less than the average total market loss ratio for policies effective during the period 9/91 to 8/93. (Ordinarily, residual market risks have loss ratios higher than the average for the total market.) In the second graph on each page, *second-report* data from Year 1 are compared to first-report data from the same policy year; generally loss ratios increase as the data mature. For the first year of QLMP, participants who continued in the QLMP through the second-report period of their first year (policy period 9/90 to 8/91) showed less of this loss ratio increase than the average for all risks, while participants who left the Program after one year showed greater loss ratio deterioration. This difference could be due in part to continuing case management by the QLMP provider or by the return-to-work component of the Program. The results for the second year of the Program (policy period 9/91 to 8/92) are approximately the same as non-QLMP participants.

Exhibits 4 and **5** separate the analysis of loss ratio improvement into, respectively, experience mod groups and premium size groups. (Loss ratios using *manual* premium are considered here, while the preceding exhibits show loss ratios using *standard* premium.) Among the experience mod groups there is essentially no difference in performance. Of the five size groups, the second-largest group (premium size \$250,000 to \$500,000) showed the least improvement. The other premium size groups showed approximately the same improvement in loss ratio. It must be noted that when these data are subdivided into five groups, each group may not have sufficient data from which to draw meaningful conclusions.

<u>Method of Analysis</u>

"Loss ratio" denotes the ratio of incurred losses to either Manual Premium (prior to the application of experience rating) or Standard Premium (after application of the experience mod). As the QLMP credits are applied to Standard Premium (plus ARAP[4] premium), comparisons using Standard Premium are probably more relevant. The advantage of considering Manual Premium is that it avoids the possible distortion caused by experience mods changing over time (they may change differently for QLMP risks than for other risks). Unfortunately, the Experience Rating system does not record Manual Premium; it uses Expected Losses (= (Payrolls / 100) x Expected Loss Rate) instead. A loss ratio using Expected Losses is not directly comparable to a loss ratio using Manual Premium, but if the Expected Loss Rates are assumed to be at the same level of adequacy as the manual rates, then we may compare *change in* a loss ratio using Expected Losses to *change in* a loss ratio using Manual Premium.

[4] All Risk Adjustment Program.

In comparing improvement in loss ratio for the QLMP dataset to that for the total market, one may interpret the result in different ways. One purpose of this study is to determine whether the premium credits granted by the Program are justified. For this purpose we calculate improvement over a "baseline". For example, if the QLMP loss ratio decreased by 30% while the total market loss ratio decreased by 20%, the "baseline" is 0.80 (= 1 - 0.20) for the total market, the result for the QLMP risks is 0.70 (= 1 - 0.30), and we say that the QLMP risks show "12.5% improvement over the baseline" (= 1 - .70/0.80). This interpretation is used in the summary table in the main text and in many of the other exhibits.

Data Used in the Evaluation

The QLMP dataset consists of Unit Statistical Plan (USP) experience for 1,803 risks who received first-year QLMP credits on policies with effective dates from September 1, 1990 through August 31, 1993. This dataset includes all QLMP participants during that period except those who:

1. Were too small to be experience-rated. (As described below, comparison data is obtained from the Bureau's experience rating system.)
2. Entered the loss management program of a qualified provider prior to May 1, 1990. (Such participants were not eligible for a first-year credit.)
3. Had no workers' compensation insurance policy prior to their credit policy, so improvement cannot be judged.

For each risk, the following USP data items were recorded:

1. Standard Premium and Subject (Manual) Premium at latest report for the Prior policy (i.e. the policy immediately before the policy receiving a first-year credit), the Year 1 policy (first-year credit), and, where applicable, the Year 2 policy and/or the Year 3

policy. (Note that the QLMP credits actually apply to Standard Premium plus ARAP premium.)

2. Incurred Losses at first report for each policy named in #1.

   Incurred Losses at second report for policies with effective dates through August 31, 1992.

   Incurred Losses at third report for policies with effective dates through August 31, 1991.

To evaluate the impact of the Program, we compared the experience of the participants to the experience for all risks (Voluntary as well as Assigned), for Assigned Risks only, or for Nonparticipants (Assigned Risks who had not participated in the Program). In each case we used data from the Experience Rating system (which is based on USP data) for the comparison. The time periods for the Experience Rating data were chosen to correspond as closely as possible to the time periods covered by the QLMP participants' policy data (Experience Rating data is organized by "mod effective date" rather than by "policy effective date").

A drawback to using "Assigned Risk" Experience Rating data is that it consists of those insureds who were in the Pool *not* on the effective date of the policy whose data are being considered, but on the mod effective date, which is generally two years later. In particular, this set of policies is not closed, i.e., the "Prior Year" data and the "Year 1" data do not come from precisely the same insureds. A different problem arises when we attempt to derive data for nonparticipants by subtracting participant data from assigned risk data. We subtracted out from the

"All Risks" those participants whose prior policies or credit policies overlap with the policy period in question. Thus, "All Risks" is approximately "All Non-QLMP" Risks.[5]

Tables of the Underlying Data

Table 4 shows raw and adjusted data comparing the QLMP dataset with the total market (experience-rated risks only). For the "first" year of the Program, 9/1/90 - 8/31/91, data was available at first, second, and third reports (Page 1). For the "second" year of first-year credits, 9/1/91 - 7/31/92 (Page 2), data was available at first and second report. For the "third" year of first-year credits, data was available at first report only. Data for risks who continued in the Program and received second-year credits are shown on Pages 4 - 7. Pages 8 and 9 show data for risks who continued in the Program and received third year credits. Significant improvement continues in the second year and third year of participation.

Table 5 compares QLMP participants to all experience-rated assigned risks and to nonparticipating assigned risks. To obtain data for nonparticipants, one must subtract from the assigned risk data not only the QLMP dataset data, but also data from those QLMP participants not included in this dataset due to entering the Program prior to 5/1/90 or to having no "Prior" policy. As discussed above, this data is available only for the "first" year of the Program. At first, second, and third report, nonparticipants showed the least loss ratio improvement among all groups studied.

Table 6 details the first-year performance of risks who stayed in the Program for second-year credit as compared to risks who left the Program after one year. **Table 6** also shows the effect of continuing participation on losses at second report (see the bottom graph of **Exhibit 3**).

[5] Due to QLMP participants' dropping out before becoming credit eligible or due to short policies, there may be some "QLMP" policies in the "Non-QLMP" set.

Table 7 displays loss ratio improvement separately for three different experience mod classes. In this analysis, higher-mod risks showed a slightly greater improvement in loss ratio to manual premium.

Table 8 compares loss ratio improvement for five different premium size groups. Again, the results are not precisely as might be expected. While four of the size groups showed approximately the same improvement (27% to 29%), the size group ($250,000 to $500,000) showed the least improvement (10%). Both here and with the mod groups, **Table 7**, the results can vary from year to year.

Reflection of QLMP impact in ratemaking

In the loss ratio method of ratemaking usually used for workers' compensation insurance, standard premiums[6] are compared to losses.[7] The QLMP credits are applied after standard premiums, and thus do not affect the reported standard premiums. However, as shown here the reported losses are lower than they would otherwise have been. Therefore, the initial impact of the QLMP was to lower loss ratios compared to where they would have otherwise been. This was judged to largely reflect a permanent improvement which would be maintained into the future,[8] i.e., risks that have completed a Qualified Loss Management Program should continue to produce the lower loss ratios observed in this study, even though they are no longer eligible for a QLMP credit. Hence, no specific adjustment was made to losses or premiums used in the rate indication in order to reflect the impact of the QLMP.

[6] Adjusted for trend, development and rate changes.

[7] Adjusted for trend, development and law changes.

[8] Usually, there is 3 or 4 years from the data used to make workers' compensation rates and the policy effective period. Thus, the assumption made was that the improvements would be maintained over this time frame.

In contrast, the QLMP does impact the calculation of loss trend. When estimating the loss trend it is necessary to put all years' experience on a common basis. In ratemaking we need to measure the long term trend in the absence of the introduction of new programs. Insureds have already received QLMP credits, and any new entrants to the Program will receive their credits. Failing to adjust for the impact of the QLMP in a calculated trend would be inappropriate double counting. The adjustment to each year's estimated ultimate losses varies with the fraction of total market premium paid by QLMP participants.

For example, assume that 15% of the total standard premium in a certain year comes from QLMP participants, and that the QLMP reduced their losses by approximately 20% below where they would otherwise have been. Then for purposes of calculating trend, one could increase the reported loss ratio for this year to what it would have been in the absence of the introduction of the QLMP. In this case, one would multiply the loss ratio for this year by a factor of $(1 - .15) + (.15)/(1 - .20) = 1.0375$. This adjustment would put this year's loss ratio on the same basis as those for older years prior to the introduction of the QLMP.

Also, the evaluation of the QLMP program made more concrete the large potential savings that could result from employing loss management techniques. Such activity was undoubtedly responsible for a large part of the improvement in experience in Workers' Compensation results so far this decade. Deciding how much of the improvement was due to such efforts is essential if one will use historical data to predict future trends.

The Program's effects may also affect the development of losses. To quantify or even verify this would require a fairly long-term study. The short-term data in Table 4 are inconclusive in this regard. If the QLMP were found -- or were assumed -- to produce a material impact on loss development, then adjustments should be made to the ratemaking procedures. As in the trend calculation, the adjustment would vary with the fraction of each year's losses incurred by QLMP participants. In Massachusetts Workers' Compensation, no such ratemaking adjustment has been made.

Conclusions

The Qualified Loss Management Program was one of many changes that ushered in the dramatic improvement in Massachusetts Workers' Compensation results shown in Exhibit 6. The evaluation presented in this paper demonstrated how significant the improvement can be from instituting this or similar cost containment programs. The general method used here can be employed to evaluate most loss control programs, if suitable data are available.

Similar evaluation techniques could be applied to other specific programs or events which influence the insurance environment. Tort law reforms passed by state legislatures which are intended to reduce the frequency and/or severity of liability verdicts are a prominent example. Evaluating these impacts is of critical importance in calculating adequate liability insurance rates. The evaluation is not as simple as that of the QLMP: because the tort reform applies to *all* insureds, there is no obvious control group to compare to. For this purpose one could identify a group of "similar" states -- that is, states with frequency or severity distributions for liability claims which are similar to those of the studied state, but which have not instituted any tort reforms. However, the available data are not likely to be as complete or as uniform as the Unit Statistical Plan and Experience Rating system data which were used in the QLMP study.

Massachusetts Workers' Compensation

Qualified Loss Management Program Credits
Estimated as of 7/15/97; premiums and credits are in thousands of dollars

	Policy Year								Total - All Policy Years
	1990	1991	1992	1993	1994	1995	1996*	1997**	
1st-Year Credits									
Number of Policies	44	691	560	932	652	239	64	1	3,183
Estimated Premium	11,987	162,187	69,677	68,171	32,417	8,162	2,022	7	354,631
Estimated Credit	904	10,030	5,018	8,926	4,728	1,182	289	1	31,078
Average Size of Risk	272	235	124	73	50	34	32	7	111
Average Credit	7.5%	6.2%	7.2%	13.1%	14.6%	14.5%	14.3%	15.0%	8.8%
2nd-Year Credits									
Number of Policies		31	552	459	832	536	138	3	2,551
Estimated Premium		10,396	108,025	59,252	51,532	26,303	4,555	64	260,127
Estimated Credit		815	8,084	6,559	7,425	3,760	647	10	27,299
Average Size of Risk		335	196	129	62	49	33	21	102
Average Credit		7.8%	7.5%	11.1%	14.4%	14.3%	14.2%	15.0%	10.5%
3rd-Year Credits									
Number of Policies			28	496	358	558	277	22	1,739
Estimated Premium			6,460	76,480	37,560	31,732	13,287	570	166,088
Estimated Credit			229	4,735	2,681	2,354	926	40	10,967
Average Size of Risk			231	154	105	57	48	26	96
Average Credit			3.5%	6.2%	7.1%	7.4%	7.0%	7.0%	6.6%
4th-Year Credits									
Number of Policies					331	193	230	31	785
Estimated Premium					35,724	17.691	10,526	1,158	65,099
Estimated Credit					1,340	630	394	41	2,405
Average Size of Risk					108	92	46	37	83
Average Credit					3.8%	3.6%	3.7%	3.5%	3.7%
Total Credits									
Number of Policies	44	722	1,140	1,887	2,173	1,526	709	57	8,258
Estimated Premium	11,987	172,583	184,161	203,902	157,233	83,888	30,389	1,799	845,944
Estimated Credit	904	10,845	13,331	20,220	16,175	7,926	2,256	91	71,749
Average Size of Risk	272	239	162	108	72	55	43	32	

* Preliminary
** Extremely Preliminary

Notes:

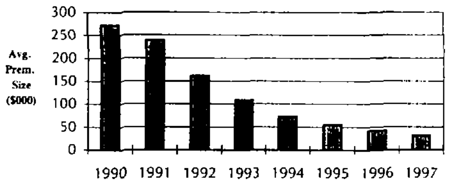
(1) The premiums and credits shown are estimated at policy inception, while the actual credits are applied at audit.
(2) Figures for recent years are understated due to substantial delays in credit applications and audits.
(3) The maximum allowable credit increased from 10% to 15% effective 1/1/93.
(4) Third-year credit is one-half of the otherwise applicable credit. Effective 1/1/94, fourth-year credit is available at one-quarter of the otherwise applicable credit.
(5) Risks who entered the Program before 5/1/90 were not eligible for first-year credit and are not included in this table.

Source: The Workers' Compensation Rating and Inspection Bureau of Massachusetts

Table 1
Page 2

Massachusetts Workers' Compensation
QLMP Policies by Size of Risk

Policy Year 1990			
Interval	Count	Premium	Share
Up to 50,000	3	72,633	1%
50,001 to 100,000	8	596,856	5%
100,001 to 250,000	21	3,201,401	27%
250,001 to 500,000	5	1,793,542	15%
500,001 to 1,000,000	4	2,675,841	22%
Over 1,000,000	3	3,647,151	30%
Total	44	11,987,424	
Average		272,441	



QLMP Average Size of Risk by Policy Year

Policy Year 1991			
Interval	Count	Premium	Share
Up to 50,000	156	4,174,649	2%
50,001 to 100,000	151	10,706,855	6%
100,001 to 250,000	236	39,717,418	23%
250,001 to 500,000	115	39,029,785	23%
500,001 to 1,000,000	45	29,491,864	17%
Over 1,000,000	19	49,462,272	29%
Total	722	172,582,843	
Average		239,034	

Policy Year 1992			
Interval	Count	Premium	Share
Up to 50,000	302	8,074,572	4%
50,001 to 100,000	282	20,195,006	11%
100,001 to 250,000	359	59,008,007	32%
250,001 to 500,000	142	49,418,117	27%
500,001 to 1,000,000	43	28,695,424	16%
Over 1,000,000	12	18,770,351	10%
Total	1,140	184,161,477	
Average		161,545	

Policy Year 1993			
Interval	Count	Premium	Share
Up to 50,000	725	19,053,936	9%
50,001 to 100,000	521	37,984,102	19%
100,001 to 250,000	478	74,633,493	37%
250,001 to 500,000	129	45,360,864	22%
500,001 to 1,000,000	29	18,259,534	9%
Over 1,000,000	5	8,610,544	4%
Total	1,887	203,902,473	
Average		108,056	

Policy Year 1994			
Interval	Count	Premium	Share
Up to 50,000	1,116	27,788,111	18%
50,001 to 100,000	584	40,559,205	26%
100,001 to 250,000	391	58,664,828	37%
250,001 to 500,000	74	24,837,958	16%
500,001 to 1,000,000	8	5,383,292	3%
Over 1,000,000	0	0	
Total	2,173	157,233,394	
Average		72,358	

Policy Year 1995			
Interval	Count	Premium	Share
Up to 50,000	976	22,847,719	27%
50,001 to 100,000	349	24,181,802	29%
100,001 to 250,000	169	24,311,140	29%
250,001 to 500,000	26	8,388,493	10%
500,001 to 1,000,000	5	2,981,691	4%
Over 1,000,000	1	1,177,281	
Total	1,526	83,888,126	
Average		54,973	

Policy Year 1996			
Interval	Count	Premium	Share
Up to 50,000	542	12,240,349	40%
50,001 to 100,000	104	6,953,793	23%
100,001 to 250,000	53	7,040,239	23%
250,001 to 500,000	7	2,242,656	7%
500,001 to 1,000,000	3	1,912,248	
Over 1,000,000	0	0	
Total	709	30,389,285	
Average		42,862	

Policy Year 1997			
Interval	Count	Premium	Share
Up to 50,000	51	1,068,863	59%
50,001 to 100,000	3	191,322	11%
100,001 to 250,000	3	538,843	30%
250,001 to 500,000	0	0	0%
500,001 to 1,000,000	0	0	
Over 1,000,000	0	0	
Total	57	1,799,028	
Average		31,562	

All Policy Years			
Interval	Count	Premium	Share
Up to 50,000	3,871	95,320,832	11%
50,001 to 100,000	2,002	141,368,941	17%
100,001 to 250,000	1,710	267,115,369	32%
250,001 to 500,000	498	171,071,415	20%
500,001 to 1,000,000	137	89,399,894	11%
Over 1,000,000	40	81,667,599	10%
Total	8,258	845,944,050	
Average		102,439	

Notes:

1. Premiums shown are Estimated Standard Premium plus ARAP, estimated at time of policy issuance.
2. Due to delays between the policy effective date and the date credit is processed, figures for 1996 are preliminary. Figures for 1997 are incomplete and are presented only to give an idea of the distribution of sizes.
3. Risks who entered the Program before 5/1/90 (not eligible for first year credit) are not included in this exhibit.

Source: Workers' Compensation Rating and Inspection Bureau of Massachusetts

Qualified Loss Management Program
Sample Calculation of Credit for a QLMP Firm

PRIOR*			SUBSEQUENT**		
(1)	Expected Losses	669,976	(1)	Expected Losses	343,184
(2)	Expected Primary	131,250	(2)	Expected Primary	67,032
(3)	Expected Excess = (1) - (2)	538,726	(3)	Expected Excess = (1) - (2)	276,152
(4)	Actual Losses	1,150,134	(4)	Actual Losses	84,725
(5)	Actual Primary	207,197	(5)	Actual Primary	33,718
(6)	Actual Excess = (4) - (5)	942,937	(6)	Actual Excess = (4) - (5)	51,007
(7)	Ballast Value	84,000	(7)	Ballast Value	52,500
(8)	Weighting Value	0.30	(8)	Weighting Value	0.21
(9B)	Modification	1.262	(9A)	Modification	0.796

Ratio (9A)/(9B) =	**0.631**
Indicated First Year Credit = 0.75 x (1 - Ratio) subject to 15% maximum	**15%**

$$\text{Modification} = \frac{(5) + [(8)\times(6)] + \{[1 - (8)] \times (3)\} + (7)}{(1) + (7)}$$

* Experience Rating data at first report for clients of the firm, for each client's policy prior to the inception of the program.

** Experience Rating data at first report for each client's policy subsequent to the inception of the program.

Massachusetts Workers' Compensation

Evaluation of Qualified Loss Management Program

	Decrease in Loss Ratio from Prior Year to Year 1	QLMP Improvement Over All Non-QLMP Risks "Baseline"
First-Year Credits, 9/90 - 8/93 first-report losses		
QLMP dataset *(1803 risks)*	30.5%	20.8%
First-Year Credits, 9/90 - 8/91 first-report losses		
QLMP dataset *(538 risks)*	23.2%	13.3%
All non-QLMP Risks	11.4%	
First-Year Credits, 9/90 - 8/91 second-report losses		
QLMP dataset	27.2%	14.7%
All non-QLMP Risks	14.7%	
First-Year Credits, 9/90 - 8/91 third-report losses		
QLMP dataset	25.9%	14.0%
All non-QLMP Risks	13.8%	
First-Year Credits, 9/91 - 8/92 first-report losses		
QLMP dataset *(527 risks)*	42.1%	28.2%
All non-QLMP Risks	19.4%	
First-Year Credits, 9/91 - 8/92 second-report losses		
QLMP dataset	38.4%	23.3%
All non-QLMP Risks	19.7%	
First-Year Credits, 9/92 - 8/93 first-report losses		
QLMP dataset *(738 risks)*	30.1%	27.9%
All non-QLMP Risks	3.0%	

Notes:

1. The QLMP dataset consists of Unit Statistical Plan Experience for 1803 experience-rated risks who received first-year credits on policies with effective dates from 9/1/90 through 8/31/93. Total Year 1 Standard Premium is $247,731,986 prior to adjustment for rate increases. Average first-year credit is 7.6%; average second year credit is 8.3%; average third year credit is 5.6%.
2. The "All Risks" set consists of Voluntary Market policies as well as Assigned Risks from the Bureau's Experience Rating System. QLMP policies are subtracted from the "All Risks" to get a true control group.
3. Loss Ratio = Incurred Losses/ Adjusted Standard Premium. Premiums are adjusted to the rate level of Policy Year 1993 to remove possible distortion caused by changing rate levels.
4. "QLMP Improvement over All-Risks Baseline" is intended to evaluate the "credit" that QLMP participants have earned over and above the loss ratio improvement seen in the total market.

Massachusetts Workers' Compensation

Evaluation of Qualified Loss Management Program

	Decrease in Loss Ratio from Prior Year to Year 2	QLMP Improvement Over All Non-QLMP Risks "Baseline"
Second-Year Credits, 9/91 - 8/92 first-report losses		
QLMP dataset *(418 risks)*	54.5%	36.3%
All non-QLMP Risks	28.6%	
Second-Year Credits, 9/91 - 8/92 second-report losses		
QLMP dataset	55.1%	34.5%
All non-QLMP Risks	31.4%	
Second-Year Credits, 9/92 - 8/93 first-report losses		
QLMP dataset *(416 risks)*	47.0%	32.3%
All non-QLMP Risks	21.8%	
	Decrease in Loss Ratio from Prior Year to Year 3	**QLMP Improvement Over All Risks "Baseline"**
Third-Year Credits, 9/92 - 8/93 first-report losses		
QLMP dataset *(327 risks)*	58.2%	39.7%
All non-QLMP Risks	30.7%	

Table 7

First-Year Credits during the period 9/1/90 - 8/31/93: Results by Experience Mod

First-Report Data; Premiums Adjusted for Rate Increases

Risks with Mod less than or equal to 1.0			*626 records from QLMP dataset*
	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	36,599,359	27,611,230	-24.6%
Standard Premium	73,837,637	73,338,607	-0.7%
Manual Premium	85,742,099	84,274,957	-1.7%
Average Experience Mod	0.86	0.89	3.9%
Average Manual Premium	136,968	134,625	-1.7%
Ratio of Incurred Losses to:			
Standard Premium	49.6%	37.6%	-24.0%
Manual Premium	42.7%	32.8%	**-23.2%**

Risks with Mod between 1.0 and 1.4			*907 records from QLMP dataset*
	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	70,750,876	51,061,382	-27.8%
Standard Premium	132,660,346	128,718,694	-3.0%
Manual Premium	120,896,263	113,547,728	-6.1%
Average Experience Mod	1.10	1.17	6.5%
Average Manual Premium	133,292	125,190	-6.1%
Ratio of Incurred Losses to:			
Standard Premium	53.3%	39.7%	-25.6%
Manual Premium	58.5%	45.0%	**-23.2%**

Risks with Mod greater than 1.4			*270 records from QLMP dataset*
	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	35,895,059	26,294,816	-26.7%
Standard Premium	55,511,175	46,339,075	-16.5%
Manual Premium	31,849,729	32,792,670	3.0%
Average Experience Mod	1.74	1.72	-1.1%
Average Manual Premium	117,962	121,454	3.0%
Ratio of Incurred Losses to:			
Standard Premium	64.7%	56.7%	-12.2%
Manual Premium	112.7%	80.2%	**-28.9%**

Data for First-Year Credits during the period 9/1/91 - 8/31/92

	First Report		Second Report	
Prior Period (9/1/90 - 8/31/91)				
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	513,733	42,260	581,098	45,367
Standard Premium*	1,230,235	70,330	1,202,609	70,330
Manual Premium*	1,277,638	70,613	1,262,222	70,613
Loss Ratio (Standard Premium)	41.8%	60.1%	48.3%	64.5%
Loss Ratio (Manual Premium)	40.2%	59.8%	46.0%	64.2%
Year 1 in Program (9/1/91 - 8/31/92)				
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	357,725	28,134	397,874	32,071
Standard Premium*	1,060,963	80,803	1,025,597	80,803
Manual Premium*	1,145,428	73,195	1,113,215	73,195
Loss Ratio (Standard Premium)	33.7%	34.8%	38.8%	39.7%
Loss Ratio (Manual Premium)	31.2%	38.4%	35.7%	43.8%
Changes, Prior Year to Year 1				
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-30.4%	-33.4%	-31.5%	-29.3%
Standard Premium	-13.8%	14.9%	-14.7%	14.9%
Manual Premium	-10.3%	3.7%	-11.8%	3.7%
Loss Ratio (Standard Premium)	-19.4%	-42.1%	-19.7%	-38.4%
Loss Ratio (Manual Premium)	-22.4%	-35.8%	-22.4%	-31.8%
Improvement Over non-QLMP risks.		**28%**		**23%**

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)

527 records in this subset of QLMP dataset

* *Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/92 - 8/31/93

Prior Period (9/1/91 - 8/31/92)		
	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	357,725	27,347
Standard Premium*	1,060,963	61,889
Manual Premium*	1,145,428	61,233
Loss Ratio (Standard Premium)	33.7%	44.2%
Loss Ratio (Manual Premium)	31.2%	44.7%

Year 1 in Program (9/1/92 - 8/31/93)		
	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	315,993	19,934
Standard Premium*	966,991	64,456
Manual Premium*	1,126,944	59,253
Loss Ratio (Standard Premium)	32.7%	30.9%
Loss Ratio (Manual Premium)	28.0%	33.6%

Changes, Prior Year to Year 1		
	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-11.7%	-27.1%
Standard Premium	-8.9%	4.1%
Manual Premium	-1.6%	-3.2%
Loss Ratio (Standard Premium)	-3.0%	-30.1%
Loss Ratio (Manual Premium)	-10.3%	-24.8%
Improvement Over non-QLMP risks.		28%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + Δ QLMP loss ratio)/(1 + Δ Non-QLMP Risks loss ratio)

738 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for Second-Year Credits w/ first year during the period 9/1/90 - 8/31/91

Prior Period (9/1/89 - 8/31/90)	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	673,815	51,046	800,866	59,521
Standard Premium*	1,428,473	77,663	1,414,417	77,663
Manual Premium*	1,538,778	72,321	1,524,128	72,321
Loss Ratio (Standard Premium)	47.2%	65.7%	56.6%	76.6%
Loss Ratio (Manual Premium)	43.8%	70.6%	52.5%	82.3%
Year 1 in Program (9/1/90 - 8/31/91)	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	513,733	39,489	581,098	43,462
Standard Premium*	1,230,235	74,622	1,202,609	74,622
Manual Premium*	1,277,638	65,757	1,262,222	65,757
Loss Ratio (Standard Premium)	41.8%	52.9%	48.3%	58.2%
Loss Ratio (Manual Premium)	40.2%	60.1%	46.0%	66.1%
Year 2 in Program (9/1/91 - 8/31/92)	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	357,725	22,472	397,874	25,854
Standard Premium*	1,060,963	75,204	1,025,597	75,204
Manual Premium*	1,145,428	62,656	1,113,215	62,656
Loss Ratio (Standard Premium)	33.7%	29.9%	38.8%	34.4%
Loss Ratio (Manual Premium)	31.2%	35.9%	35.7%	41.3%

418 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for Second-Year Credits w/ first year during the period 9/1/90 - 8/31/91

Changes, Prior Period to Year 1

	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-23.8%	-22.6%	-27.4%	-27.0%
Standard Premium*	-13.9%	-3.9%	-15.0%	-3.9%
Manual Premium*	-17.0%	-9.1%	-17.2%	-9.1%
Loss Ratio (Standard Premium)	-11.4%	-19.5%	-14.7%	-24.0%
Loss Ratio (Manual Premium)	-8.2%	-14.9%	-12.4%	-19.7%

Changes, Year 1 to Year 2

	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-30.4%	-43.1%	-31.5%	-40.5%
Standard Premium*	-13.8%	0.8%	-14.7%	0.8%
Manual Premium*	-10.3%	-4.7%	-11.8%	-4.7%
Loss Ratio (Standard Premium)	-19.4%	-43.5%	-19.7%	-40.9%
Loss Ratio (Manual Premium)	-22.4%	-40.3%	-22.4%	-37.5%

Changes, Prior Period to Year 2

	First Report		Second Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-46.9%	-56.0%	-50.3%	-56.6%
Standard Premium*	-25.7%	-3.2%	-27.5%	-3.2%
Manual Premium*	-25.6%	-13.4%	-27.0%	-13.4%
Loss Ratio (Standard Premium)	-28.6%	-54.5%	-31.4%	-55.1%
Loss Ratio (Manual Premium)	-28.8%	-49.2%	-32.0%	-49.8%
Improvement Over non-QLMP risks Prior to Year 1.		9%		11%
Improvement Over non-QLMP risks Prior to Year 2.		36%		34%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)
418 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for Second-Year Credits w/ first year during the period 9/1/91 - 8/31/92

Prior Period (9/1/90 - 8/31/91)

	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	513,733	30,720
Standard Premium*	1,230,235	51,992
Manual Premium*	1,277,638	51,829
Loss Ratio (Standard Premium)	41.8%	59.1%
Loss Ratio (Manual Premium)	40.2%	59.3%

Year 1 in Program (9/1/91 - 8/31/92)

	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	357,725	20,804
Standard Premium*	1,060,963	57,175
Manual Premium*	1,145,428	52,889
Loss Ratio (Standard Premium)	33.7%	36.4%
Loss Ratio (Manual Premium)	31.2%	39.3%

Year 2 in Program (9/1/92 - 8/31/93)

	First Report	
	Non-QLMP Risks	QLMP Dataset
Incurred Losses	315,993	17,419
Standard Premium	966,991	55,566
Manual Premium	1,126,944	50,839
Loss Ratio (Standard Premium)	32.7%	31.3%
Loss Ratio (Manual Premium)	28.0%	34.3%

416 records in this subset of QLMP dataset

* *Premium data is adjusted for rate increases.*

Reported data in $000

Data for Second-Year Credits w/ first year during the period 9/1/91 - 8/31/92

Changes, Prior Period to Year 1

	First Report Non-QLMP Risks	First Report QLMP Dataset
Incurred Losses	-30.4%	-32.3%
Standard Premium*	-13.8%	10.0%
Manual Premium*	-10.3%	2.0%
Loss Ratio (Standard Premium)	-19.4%	-38.4%
Loss Ratio (Manual Premium)	-22.4%	-33.7%

Changes, Year 1 to Year 2

	First Report Non-QLMP Risks	First Report QLMP Dataset
Incurred Losses	-11.7%	-16.3%
Standard Premium*	-8.9%	-2.8%
Manual Premium*	-1.6%	-3.9%
Loss Ratio (Standard Premium)	-3.0%	-14.0%
Loss Ratio (Manual Premium)	-10.3%	-12.7%

Changes, Prior Period to Year 2

	First Report Non-QLMP Risks	First Report QLMP Dataset
Incurred Losses	-38.5%	-43.3%
Standard Premium*	-21.4%	6.9%
Manual Premium*	-11.8%	-1.9%
Loss Ratio (Standard Premium)	-21.8%	-47.0%
Loss Ratio (Manual Premium)	-30.3%	-42.2%

Improvement Over non-QLMP risks Prior to Year 1.	24%
Improvement Over non-QLMP risks Prior to Year 2.	32%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + Δ QLMP loss ratio)/(1 + Δ Non-QLMP Risks loss ratio)
416 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for Third-Year Credits w/ first year during the period 9/1/90 - 8/31/91

	Prior Period (9/1/89 - 8/31/90)		*Year 1 (9/1/90 - 8/31/91)*	
	First Report		First Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	673,815	32,548	513,733	25,586
Standard Premium*	1,428,473	52,054	1,230,235	48,398
Manual Premium*	1,538,778	48,767	1,277,638	43,202
Loss Ratio (Standard Premium)	47.2%	62.5%	41.8%	52.9%
Loss Ratio (Manual Premium)	43.8%	66.7%	40.2%	59.2%

	Year 2 (9/1/91 - 8/31/92)		*Year 3 (9/1/92 - 8/31/93)*	
	First Report		First Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	357,725	22,472	315,993	12,138
Standard Premium*	1,060,963	75,204	966,991	46,427
Manual Premium*	1,145,428	62,656	1,126,944	39,917
Loss Ratio (Standard Premium)	33.7%	29.9%	32.7%	26.1%
Loss Ratio (Manual Premium)	31.2%	35.9%	28.0%	30.4%

327 records in this subset of QLMP dataset

* *Premium data is adjusted for rate increases.*

Reported data in $000

Data for Third-Year Credits w/ first year during the period 9/1/90 - 8/31/91

	Changes, Prior to Year 1		Changes, Year 1 to Year 2	
	First Report		First Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-23.8%	-21.4%	-30.4%	-12.2%
Standard Premium*	-13.9%	-7.0%	-13.8%	55.4%
Manual Premium*	-17.0%	-11.4%	-10.3%	45.0%
Loss Ratio (Standard Premium)	-11.4%	-15.4%	-19.4%	-43.5%
Loss Ratio (Manual Premium)	-8.2%	-11.2%	-22.4%	-39.4%

	Changes, Prior to Year 2		Changes, Year 2 to Year 3	
	First Report		First Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-46.9%	-31.0%	-11.7%	-46.0%
Standard Premium*	-25.7%	44.5%	-8.9%	-38.3%
Manual Premium*	-25.6%	28.5%	-1.6%	-36.3%
Loss Ratio (Standard Premium)	-28.6%	-52.2%	-3.0%	-12.7%
Loss Ratio (Manual Premium)	-28.8%	-46.2%	-10.3%	-15.3%

	Changes, Prior to Year 3		Changes, Year 1 to Year 3	
	First Report		First Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-53.1%	-62.7%	-38.5%	-52.6%
Standard Premium*	-32.3%	-10.8%	-21.4%	-4.1%
Manual Premium*	-26.8%	-18.1%	-11.8%	-7.6%
Loss Ratio (Standard Premium)	-30.7%	-58.2%	-21.8%	-50.7%
Loss Ratio (Manual Premium)	-36.1%	-54.4%	-30.3%	-48.6%

Improvement Over non-QLMP risks Prior to Year 1.	4%
Improvement Over non-QLMP risks Prior to Year 2.	33%
Improvement Over non-QLMP risks Prior to Year 3.	40%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)
416 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/90 - 8/31/91

Prior Period (9/1/89 - 8/31/90)	First Report		Second Report		Third Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	353,527	73,639	400,976	86,754	287,970	91,100
Standard Premium*	668,176	116,178	658,970	116,178	451,198	116,178
Manual Premium*	714,417	106,641	708,850	106,641	490,427	106,641
Loss Ratio (Standard Premium)	52.9%	63.4%	60.8%	74.7%	63.8%	78.4%
Loss Ratio (Manual Premium)	49.5%	69.1%	56.6%	81.4%	58.7%	85.4%

Year 1 in Program (9/1/90 - 8/31/91)	First Report		Second Report		Third Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	251,111	56,899	208,047	63,529	91,359	67,849
Standard Premium*	515,452	116,750	363,464	116,750	133,486	116,750
Manual Premium*	546,400	98,167	391,526	98,167	157,928	98,167
Loss Ratio (Standard Premium)	48.7%	48.7%	57.2%	54.4%	68.4%	58.1%
Loss Ratio (Manual Premium)	46.0%	58.0%	53.1%	64.7%	57.8%	69.1%

Changes, Prior Year to Year 1	First Report		Second Report		Third Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	-29.0%	-22.7%	-48.1%	-26.8%	-68.3%	-25.5%
Standard Premium	-22.9%	0.5%	-44.8%	0.5%	-70.4%	0.5%
Manual Premium	-23.5%	-7.9%	-44.8%	-7.9%	-67.8%	-7.9%
Loss Ratio (Standard Premium)	-7.9%	-23.2%	-5.9%	-27.2%	7.2%	-25.9%
Loss Ratio (Manual Premium)	-7.1%	-16.1%	-6.2%	-20.5%	-1.5%	-19.1%
Improvement Over non-QLMP risks.		17%		23%		31%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.

Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)

538 records in this subset of QLMP dataset

* *Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/91 - 8/31/92

	First Report		Second Report	
Prior Period (9/1/90 - 8/31/91)				
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	251,111	42,260	208,047	45,367
Standard Premium*	515,452	70,330	363,464	70,330
Manual Premium*	546,400	70,613	391,526	70,613
Loss Ratio (Standard Premium)	48.7%	60.1%	57.2%	64.5%
Loss Ratio (Manual Premium)	46.0%	59.8%	53.1%	64.2%
Year 1 in Program (9/1/91 - 8/31/92)				
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	129,424	28,134	76,159	32,071
Standard Premium*	344,427	80,803	140,859	80,803
Manual Premium*	338,596	73,195	135,335	73,195
Loss Ratio (Standard Premium)	37.6%	34.8%	54.1%	39.7%
Loss Ratio (Manual Premium)	38.2%	38.4%	56.3%	43.8%
Changes, Prior Year to Year 1				
	Non-QLMP Assigned Risks	QLMP Dataset Risks	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	-48.5%	-33.4%	-63.4%	-29.3%
Standard Premium	-33.2%	14.9%	-61.2%	14.9%
Manual Premium	-38.0%	3.7%	-65.4%	3.7%
Loss Ratio (Standard Premium)	-22.8%	-42.1%	-5.4%	-38.4%
Loss Ratio (Manual Premium)	-17.0%	-35.8%	6.0%	-31.8%
Improvement Over non-QLMP risks.		25%		35%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)

538 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/92 - 8/31/93

Prior Period (9/1/91 - 8/31/92)		
	First Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	129,424	27,347
Standard Premium*	344,427	61,889
Manual Premium*	338,596	61,233
Loss Ratio (Standard Premium)	37.6%	44.2%
Loss Ratio (Manual Premium)	38.2%	44.7%
Year 1 in Program (9/1/92 - 8/31/93)		
	First Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	96,695	19,934
Standard Premium*	200,740	64,456
Manual Premium*	210,867	59,253
Loss Ratio (Standard Premium)	48.2%	30.9%
Loss Ratio (Manual Premium)	45.9%	33.6%
Changes, Prior Year to Year 1		
	First Report	
	Non-QLMP Assigned Risks	QLMP Dataset Risks
Incurred Losses	-25.3%	-27.1%
Standard Premium	-41.7%	4.1%
Manual Premium	-37.7%	-3.2%
Loss Ratio (Standard Premium)	28.2%	-30.1%
Loss Ratio (Manual Premium)	20.2%	-24.8%
Improvement Over non-QLMP risks.		45%

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)

538 records in this subset of QLMP dataset

* *Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/90 - 8/31/91

Prior Period (9/1/89 - 8/31/90)

	Risks who participated in Second Year of QLMP			Risks who **did not** participate in Second Year of QLMP		
	Rept. 1	Rept. 2	Rept. 3	Rept. 1	Rept. 2	Rept. 3
Incurred Losses	51,046	59,521	62,102	22,592	27,232	28,999
Standard Premium*	77,663	77,663	77,663	38,515	38,515	38,515
Manual Premium*	72,321	72,321	72,321	34,320	34,320	34,320
Loss Ratio (Standard Premium)	65.7%	76.6%	80.0%	58.7%	70.7%	75.3%
Loss Ratio (Manual Premium)	70.6%	82.3%	85.9%	65.8%	79.3%	84.5%
Loss Ratio(Standard Premium) Change from Rept. 1		**16.6%**	**21.8%**		**20.4%**	**28.3%**

Year 1 in Program (9/1/90 - 8/31/91)

	Risks who participated in Second Year of QLMP			Risks who **did not** participate in Second Year of QLMP		
	Rept. 1	Rept. 2	Rept. 3	Rept. 1	Rept. 2	Rept. 3
Incurred Losses	39,489	43,462	46,218	17,410	20,066	21,632
Standard Premium*	74,622	74,622	74,622	42,128	42,128	42,128
Manual Premium*	65,757	65,757	65,757	32,410	32,410	32,410
Loss Ratio (Standard Premium)	52.9%	58.2%	61.9%	41.3%	47.6%	51.3%
Loss Ratio (Manual Premium)	60.1%	66.1%	70.3%	53.7%	61.9%	66.7%
Loss Ratio(Standard Premium) Change from Rept. 1		**10.0%**	**17.0%**		**15.3%**	**24.2%**

Data for First-Year Credits during the period 9/1/91 - 8/31/92

Prior Period (9/1/90 - 8/31/91)

	Risks who participated in Second Year of QLMP			Risks who **did not** participate in Second Year of QLMP		
	Rept. 1	Rept. 2	Rept. 3	Rept. 1	Rept. 2	Rept. 3
Incurred Losses	30,720	33,526	35,284	11,539	11,842	12,865
Standard Premium*	51,992	51,992	51,992	18,338	18,338	18,338
Manual Premium*	51,829	51,829	51,829	18,784	18,784	18,784
Loss Ratio (Standard Premium)	59.1%	64.5%	67.9%	62.9%	64.6%	70.2%
Loss Ratio (Manual Premium)	59.3%	64.7%	68.1%	61.4%	63.0%	68.5%
Loss Ratio(Standard Premium) Change from Rept. 1		**9.1%**	**14.9%**		**2.7%**	**11.6%**

Year 1 in Program (9/1/91 - 8/31/92)

	Risks who participated in Second Year of QLMP			Risks who **did not** participate in Second Year of QLMP		
	Rept. 1	Rept. 2	Rept. 3	Rept. 1	Rept. 2	Rept. 3
Incurred Losses	20,804	24,009		7,330	8,062	
Standard Premium*	57,175	57,175		23,628	23,628	
Manual Premium*	52,889	52,889		20,307	20,307	
Loss Ratio (Standard Premium)	36.4%	42.0%		31.0%	34.1%	
Loss Ratio (Manual Premium)	39.3%	45.4%		36.1%	39.7%	
Loss Ratio(Standard Premium) Change from Rept. 1		**15.4%**			**10.0%**	

** Premium data is adjusted for rate increases.*

Reported data in $000

Data for First-Year Credits during the period 9/1/90 - 8/31/91

Prior Period (9/1/89 - 8/31/90)

	First Report		Second Report		Third Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	673,815	73,639	800,866	86,754	742,953	91,100
Standard Premium*	1,428,473	116,178	1,414,417	116,178	1,281,974	116,178
Manual Premium*	1,538,778	106,641	1,524,128	106,641	1,383,987	106,641
Loss Ratio (Standard Premium)	47.2%	63.4%	56.6%	74.7%	58.0%	78.4%
Loss Ratio (Manual Premium)	43.8%	69.1%	52.5%	81.4%	53.7%	85.4%

Year 1 in Program (9/1/90 - 8/31/91)

	First Report		Second Report		Third Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	513,733	56,899	581,098	63,529.	541,312	67,849
Standard Premium*	1,230,235	116,750	1,202,609	116,750	1,082,027	116,750
Manual Premium*	1,277,638	98,167	1,262,222	98,167	1,128,023	98,167
Loss Ratio (Standard Premium)	41.8%	48.7%	48.3%	54.4%	50.0%	58.1%
Loss Ratio (Manual Premium)	40.2%	58.0%	46.0%	64.7%	48.0%	69.1%

Changes, Prior Year to Year 1

	First Report		Second Report		Third Report	
	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset	Non-QLMP Risks	QLMP Dataset
Incurred Losses	-23.8%	-22.7%	-27.4%	-26.8%	-27.1%	-25.5%
Standard Premium	-13.9%	0.5%	-15.0%	0.5%	-15.6%	0.5%
Manual Premium	-17.0%	-7.9%	-17.2%	-7.9%	-18.5%	-7.9%
Loss Ratio (Standard Premium)	-11.4%	-23.2%	-14.7%	-27.2%	-13.8%	-25.9%
Loss Ratio (Manual Premium)	-8.2%	-16.1%	-12.4%	-20.5%	-10.6%	-19.1%
Improvement Over non-QLMP risks.		**13%**		**15%**		**14%**

Comparison based on Loss Ratios to Standard Premium adjusted for rate changes.
Improvement = 1-(1 + ΔQLMP loss ratio)/(1 + ΔNon-QLMP Risks loss ratio)

538 records in this subset of QLMP dataset

** Premium data is adjusted for rate increases.*

Reported data in $000

Table 8

First-Year Credits during the period 9/1/90 - 8/31/93: Results by Manual Premium Size

First-Report Data; Premiums Adjusted for Rate Increases

Risks with Premium less than or equal to $50,000 — *669 records from QLMP dataset*

	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	18,341,217	9,975,950	-45.6%
Standard Premium	27,089,628	22,671,821	-16.3%
Manual Premium	25,305,013	18,833,351	-25.6%
Average Experience Mod	1.07	1.21	13.1%
Average Manual Premium	37,825	28,151	-25.6%
Standard Premium	67.7%	44.0%	-35.0%
Manual Premium	72.5%	53.0%	**-26.9%**

Risks with Premium between $50,000 and $100,000 — *471 records from QLMP dataset*

	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	20,888,724	13,695,305	-34.4%
Standard Premium	39,882,431	39,110,364	-1.9%
Manual Premium	36,624,098	34,021,861	-7.1%
Average Experience Mod	1.09	1.15	5.2%
Average Manual Premium	77,758	72,233	-7.1%
Loss Ratio to Standard Premium	52.4%	35.0%	-33.1%
Loss Ratio to Manual Premium	57.0%	40.3%	**-29.4%**

Risks with Premium between $100,000 and $250,000 — *447 records from QLMP dataset*

	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	40,544,013	29,047,019	-28.4%
Standard Premium	74,014,269	77,228,711	4.3%
Manual Premium	70,822,998	70,031,835	-1.1%
Average Experience Mod	1.05	1.10	4.9%
Average Manual Premium	158,441	156,671	-1.1%
Loss Ratio to Standard Premium	54.8%	37.6%	-31.3%
Loss Ratio to Manual Premium	57.2%	41.5%	**-27.5%**

Risks with Premium between $250,000 and $500,000 — *158 records from QLMP dataset*

	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	32,402,047	27,774,038	-14.3%
Standard Premium	57,578,773	58,595,584	1.8%
Manual Premium	56,297,049	53,818,071	-4.4%
Average Experience Mod	1.02	1.09	7.1%
Average Manual Premium	356,310	340,621	-4.4%
Loss Ratio to Standard Premium	56.3%	47.4%	-15.8%
Loss Ratio to Manual Premium	57.6%	51.6%	**-10.3%**

Risks with Premium over $500,000 — *58 records from QLMP dataset*

	Year Prior to QLMP	Year 1 in QLMP	Change from Prior to 1st
Incurred Losses	31,069,293	24,475,116	-21.2%
Standard Premium	49,831,276	64,402,678	29.2%
Manual Premium	49,438,933	53,910,237	9.0%
Average Experience Mod	1.01	1.19	17.8%
Average Manual Premium	852,395	929,487	9.0%
Loss Ratio to Standard Premium	62.3%	38.0%	-39.0%
Loss Ratio to Manual Premium	62.8%	45.4%	**-27.8%**

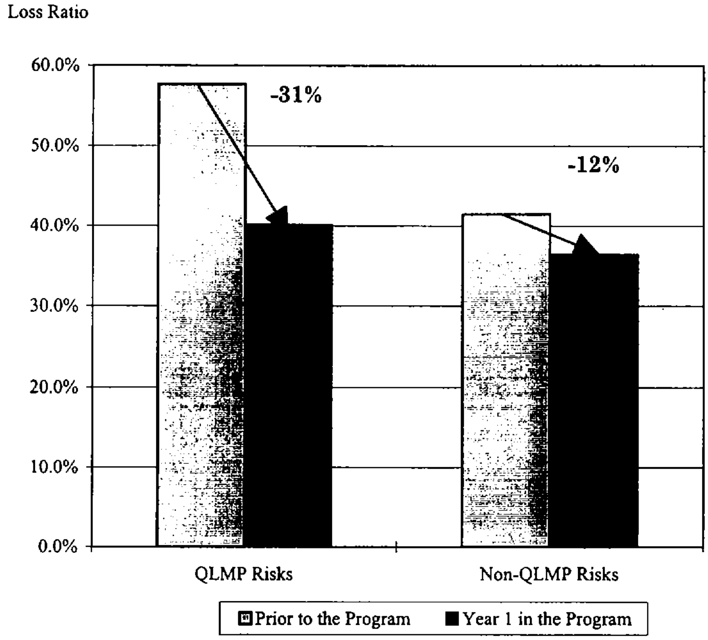
Exhibit 1

Massachusetts Workers' Compensation

Evaluation of Qualified Loss Management Program

Improvement in Loss Ratio to Standard Premium: QLMP vs "All Risks"

Year 1 Policies Effective 9/1/90 through 8/31/93



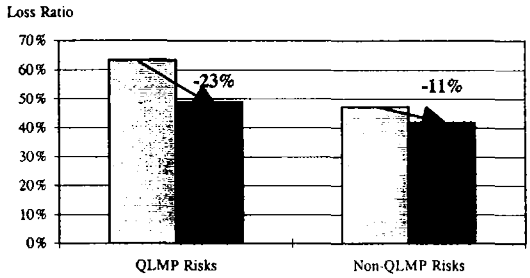
QLMP Participants showed improvement of 20.8% over the baseline total market improvement in Loss Ratio.

"All Risks" comprise of all Voluntary and Assigned Risks not associated with those participating in the QLMP program. Premiums are adjusted for rate increases. Losses are at first report.

Massachusetts Workers' Compensation
Evaluation of Qualified Loss Management Program
Continuing Improvement in Loss Ratio

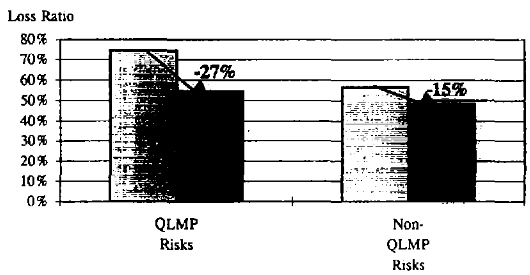
First Year Credit Period 9/1/90 through 8/31/91

First Report Data



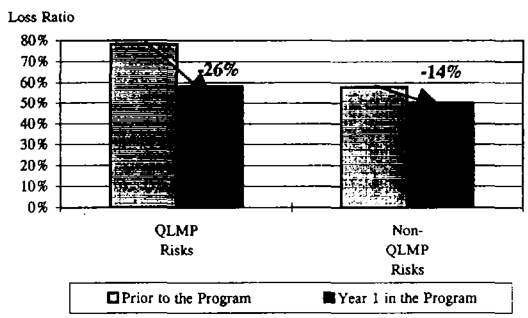
QLMP participants showed 13% more improvement over non-QLMP risks at first report.

Second Report Data



QLMP participants showed 15% more improvement over non-QLMP risks at second report.

Third Report Data

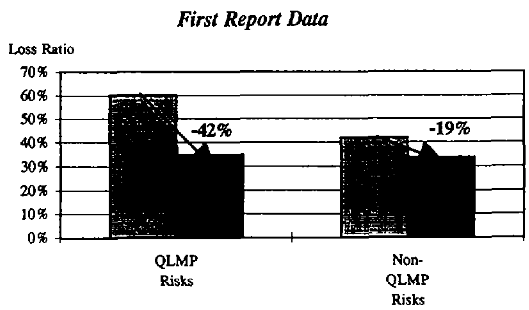


QLMP participants showed 14% more improvement over non-QLMP risks at third report.

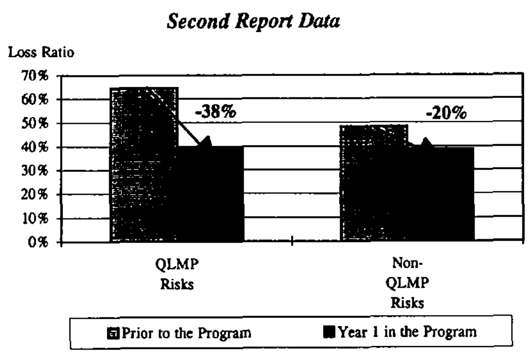
QLMP Risks are those who received first-year credit during the period 9/1/90 to 8/31/91.
All Risks are those risks for the same time period not in the QLMP program.
Loss Ratios are to Standard Premium adjusted for rate increases.

Massachusetts Workers' Compensation
Evaluation of Qualified Loss Management Program
Continuing Improvement in Loss Ratio

First Year Credit Period 9/1/91 through 8/31/92



QLMP participants showed 28% more improvement over non-QLMP risks at first report.



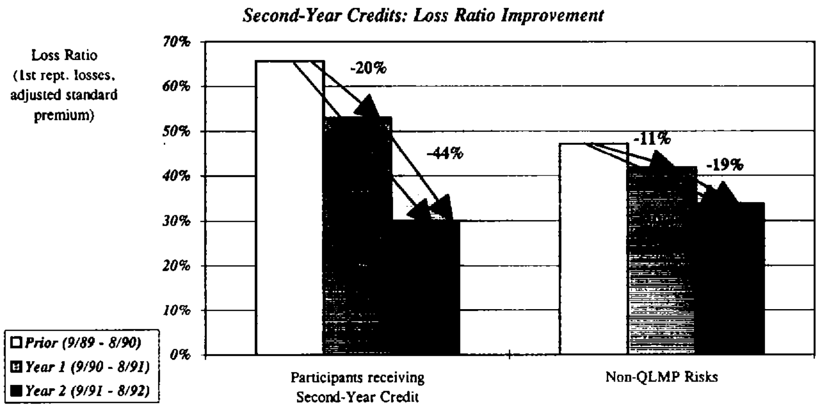
QLMP participants showed 23% more improvement over non-QLMP risks at second report.

QLMP Risks are those who received first-year credit during the period 9/1/91 to 8/31/92.
All Risks are those risks for the same time period not in the QLMP program.
Loss Ratios are to Standard Premium adjusted for rate increases.

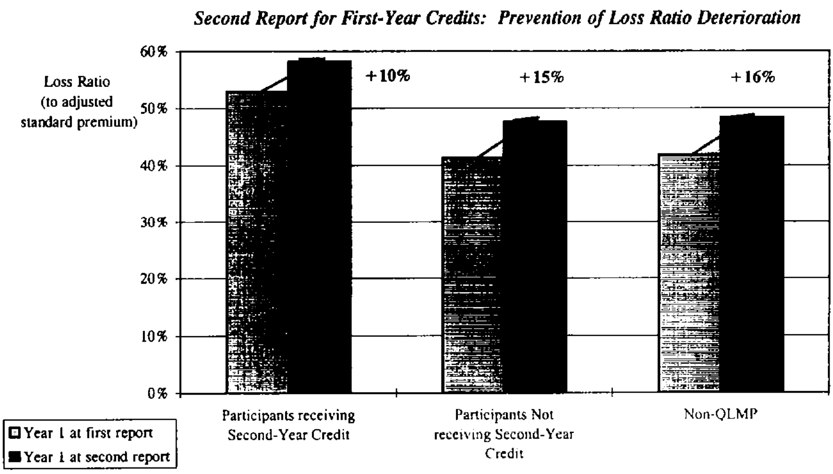
Exhibit 3
Page 1

Massachusetts Workers' Compensation
Evaluation of Qualified Loss Management Program
Effects of the Second Year of Participation in QLMP

First Year Credit Period 9/1/90 through 8/31/91



Relative to the "All Risks" loss ratio decrease over this two-year period, Second-Year QLMP participants showed better improvement by 36%.

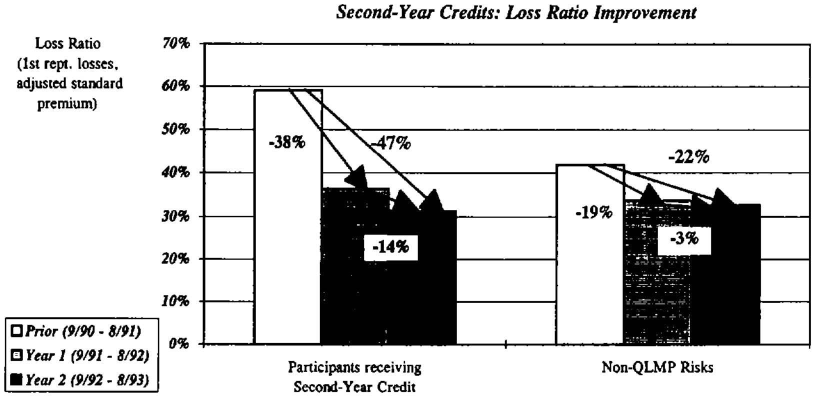


Participants who continued in the Program showed less deterioration in loss ratio at second report.

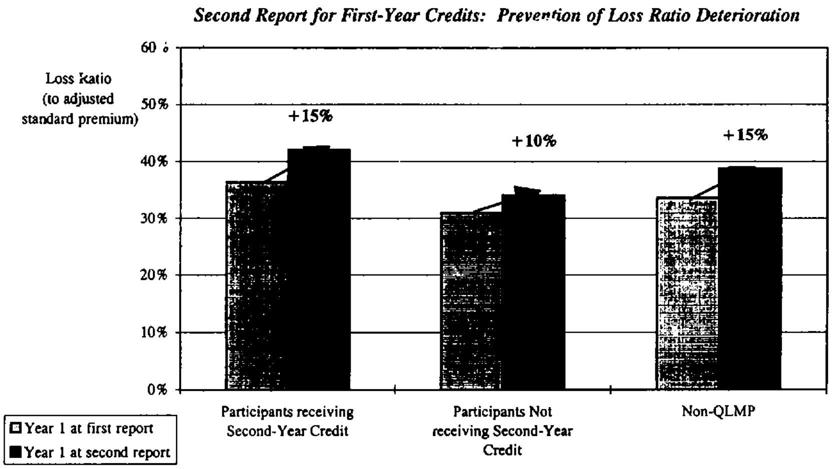
Massachusetts Workers' Compensation
Evaluation of Qualified Loss Management Program

Effects of the Second Year of Participation in QLMP

First Year Credit Period 9/1/91 through 8/31/92



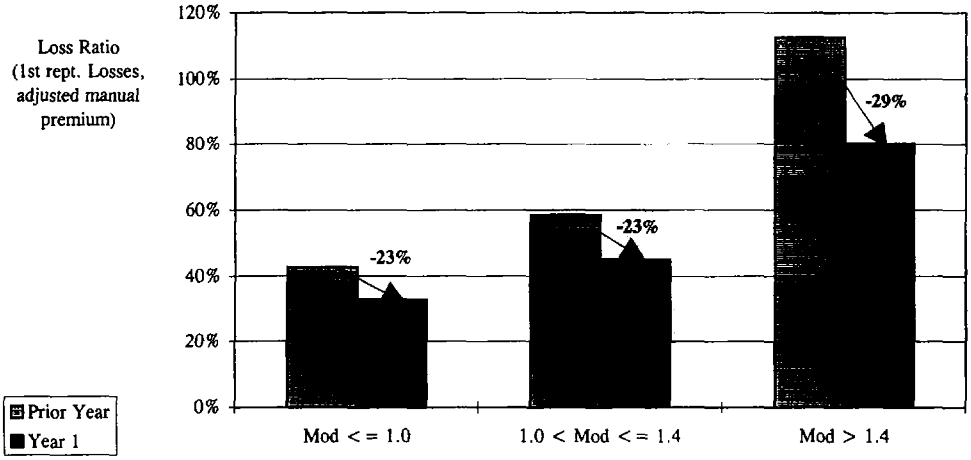
Relative to the "All Risks" loss ratio decrease over this two-year period, Second-Year QLMP participants showed better improvement by 32%.



Massachusetts Workers' Compensation
Qualified Loss Management Program Evaluation

Analysis by Experience Mod

"Mod" = Standard Premium in Year 1 / Manual Premium in Year 1



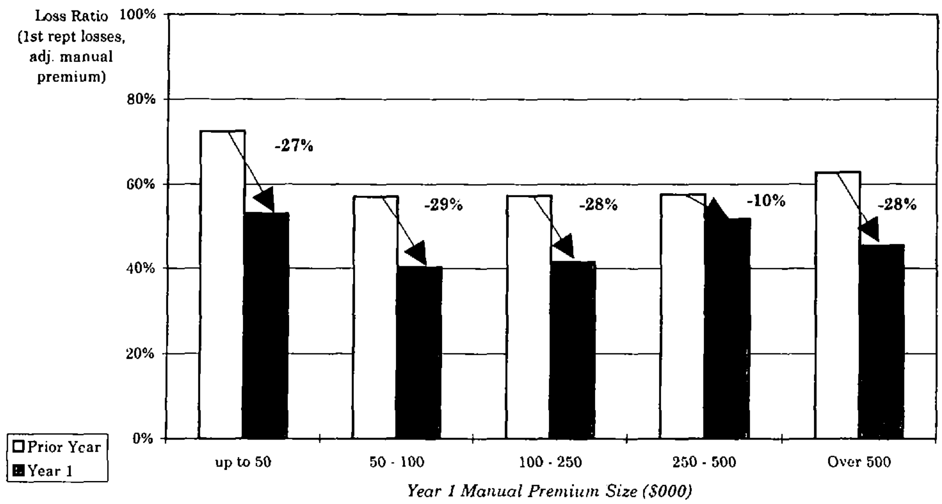
Characteristics of Mod Classes

	Mod < = 1.0	1.0 < Mod < = 1.4	Mod > 1.4
Manual Premium by Mod Year 1 in Program	$84,274,957	$113,547,728	$32,792,670
Number of Risks	626	907	270
Average Manual Premium – Year 1	$134,625	$125,190	$121,454
Average Mod – Year 1	0.89	1.17	1.72
% (of eliglible Year 1 Premium) that received Year 2 Credit	78%	72%	48%
Average Year 1 Manual Premium for Risks **with** Year 2 Credit	$168,430	$139,438	$95,135
Average Year 1 Manual Premium for Risks **without** Year 2 Credit	$147,196	$172,392	$534,725

* *Calculated for participants during the "first year" of the Program, i.e. 9/90 - 8/92, for whom Year 2 data would be available. By contrast, the first four rows include all years of the program, 9/90 - 8/93.*

Massachusetts Workers' Compensation
Qualified Loss Management Program Evaluation

Analysis by Premium Size
Manual Premium in Year 1, Adjusted for Rate Increases



Characteristics of Size Classes

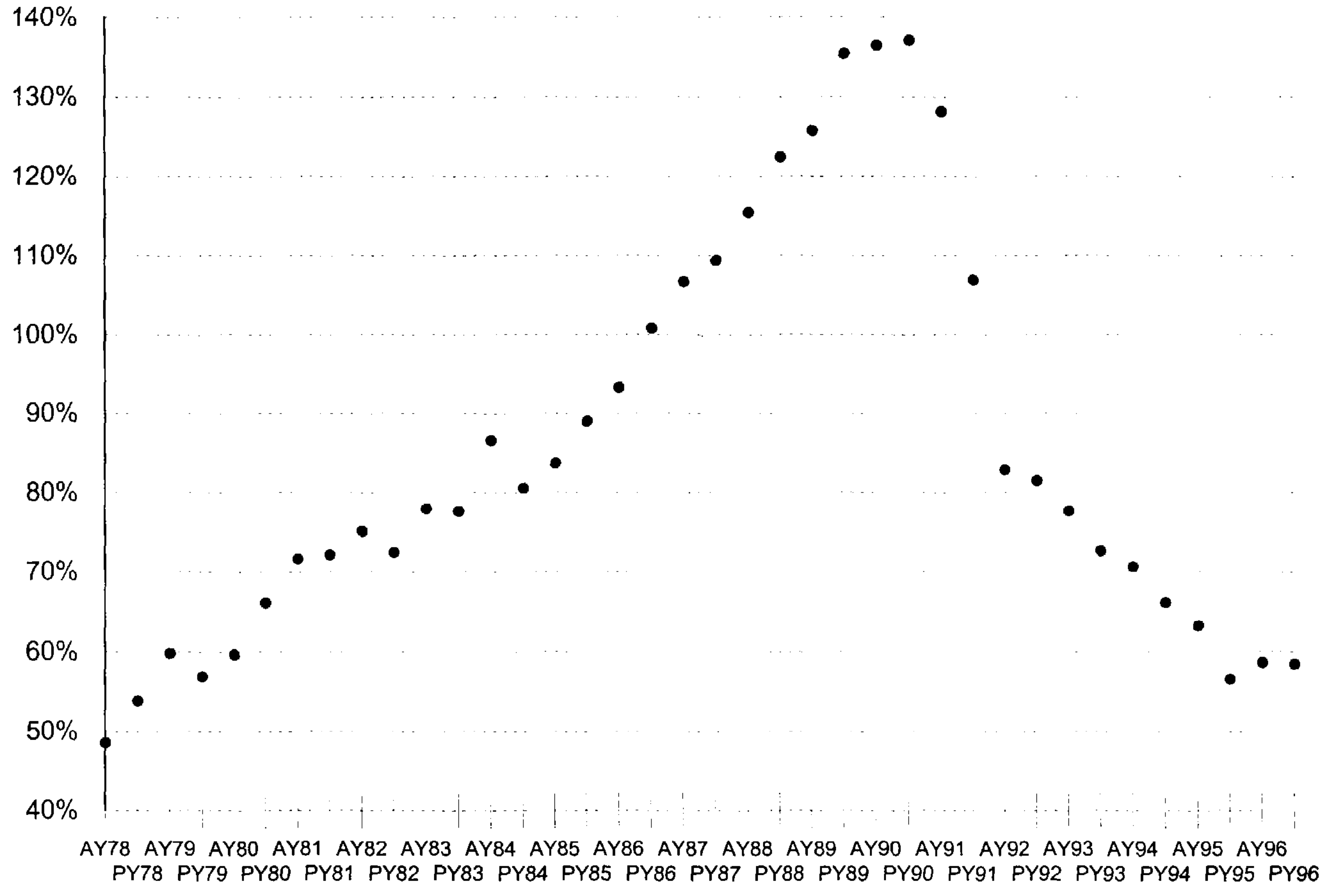
	up to 50	50 - 100	100 - 250	250 - 500	Over 500
Manual Premium Year 1 in Program	$18,833,351	$34,021,861	$70,031,835	$53,818,071	$53,910,237
Number of Risks	669	471	447	158	58
Average Manual Premium Year 1	$28,151	$72,233	$156,671	$340,621	$929,487
Avgerage Mod, Year 1	1.21	1.15	1.10	1.09	1.19
% (of Year 1 Premium) that received Year 2 Credit	79%	81%	77%	78%	54%

* *Calculated for participants during the "first year" of the Program, i.e. 9/90 - 8/92, for whom Year 2 data would be available.*

Massachusetts Workers' Compensation

Exhibit 6

On 2/14/98 Rate Level, Estimated Ultimate Loss Ratios



SUMMARY OF QUALIFIED LOSS MANAGEMENT PROGRAM

EFFECTIVE DATE:

This Program applies to new and renewal business written under the Massachusetts Workers' Compensation Assigned Risk Pool on and after 12:01 A.M., November 1, 1990.

Policyholders whose policies are effective on and after 12:01 A.M., January 1, 1993, who, while in the Pool, become credit eligible and subsequently move to the voluntary market, shall, if insured under a guaranteed cost plan, remain subject to the rules of the Program and shall be entitled to receive whatever credit eligible policyholders on such plan in the Pool may receive; provided, however, that the combined period of assigned risk pool and voluntary market credit eligibility shall not exceed forty-eight months.

All new and renewal policies effective on and after 12:01 A.M., January 1, 1993, shall be subject to a maximum credit of 15% pursuant to Section 3.b.

PURPOSE:

This Program applies a prospective credit to the premium of an assigned risk insured who subscribes to a qualified loss management program. The prospective credit is given for a period of up to four policy years, provided the insured remains in the Program for a corresponding period of time.

BACKGROUND:

A number of loss management firms have demonstrated an ability to significantly reduce workers' compensation losses for their client companies by implementing a loss control management program. Through the application of the experience rating plan, companies with improved experience are able to realize sizable reductions in premium. However, because the experience rating plan requires three years of experience and the evaluation of data six months after expiration of the third policy year, such improved experience is not reflected in the premium charges for a considerable length of time. Utilization of this Program can impact a subscribing employer's premium charges as early as the inception date of the first of four annual policy periods during which the subscribing employer completes a minimum of six months participation in the Program. The appropriate credits are applied to the premiums for these four annual policy periods, at the conclusion of which, the credits then end and the subscribing employer enters into an experience rating period with anticipated improved experience.

Approval of Loss Management Program and Available Credit

A loss management program and the amount of allowable credit that can be offered by a sponsoring loss management firm to subscribing employers shall be subject to the approval of the Workers' Compensation Rating and Inspection Bureau of Massachusetts. The credit shall be primarily determined by the loss reduction success experienced by all of the subscribing employers of the sponsoring loss management firm for the past seven years. The approved credit is applied uniformly to the premiums of all subscribing employers.

Application of Credit to Subscriber's Policy

A credit is applied to the premium developed for a subscribing employer for up to four policy years. The amount of the credit applied to the first policy year is based on the credit factor assigned to the loss management firm on the date the employer subscribes to the Program. The first year credit is applied retroactively to the policy inception date on condition the employer participates in the Program a minimum of six months.

The amount of the credit applied to the second, third and fourth policy years shall be based on the credit factor assigned to the qualifying loss management firm and in effect on each policy effective date, except that the applicable credit is halved in the third policy year and shall be 25% of the otherwise applicable credit in the fourth policy year.

The subscribing employer may terminate participation in the Program upon four years of continuous participation in the Program, without penalty.

1. Qualifications For Loss Management Firms

Any loss management firm, which has demonstrated an ability to reduce losses for its client employers, may submit a Loss Management Program to The Workers' Compensation Rating and Inspection Bureau of Massachusetts for approval, subject to its having met the following minimum qualifications.

a. Personnel

A loss management firm must evidence its ability to perform its services based upon the qualifications of its key operating personnel. Information must be submitted on the job-related training and experience of these personnel. There also should be credentialed specialists on the staff. These could include: certified safety professionals, board-certified rehabilitation specialists, licensed insurance advisors and medical doctors specializing in occupational health.

b. Safety

A loss management firm must have a structured approach in place which focuses top level management of the employer, as well as other personnel, on the issue of safety. There must be a means of measuring and insuring management commitment to implementing safe work practices in the client employer's workplace.

c. Post Injury Response

A Loss Management Program must contain plans of action and specific techniques which are designed to assist an injured worker in obtaining necessary medical care. It must also contain specified means of maintaining contact with the insured worker and continuing claims control throughout the recuperation period. A close relationship with medical providers should be included in this process.

d. Early Return to Work Provisions

A Loss Management Program must encourage an injured worker to return to work at the earliest possible time, even if it is in a modified capacity.

2. Submission of Loss Management Program For Approval

In order to offer a credit to its client employers, a loss management firm must submit to and receive approval of a Loss Management Program from The Workers' Compensation Rating and Inspection Bureau of Massachusetts following the procedures outlined below and containing the key elements indicated.

a. A Loss Management Program containing essential information shall be submitted to The Workers' Compensation Rating and Inspection Bureau of Massachusetts with sufficient lead time for proper evaluation and determination of a credit prior to implementation.

b. After evaluation of the Loss Management Program, The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall make a determination as to its acceptability. If acceptable, The Workers' Compensation Rating and Inspection Bureau of Massachusetts will calculate the credit applicable to the program for a period of one year and advise the loss management firm submitting the program, and the Massachusetts Division of Insurance, of its approval

The loss management firm shall then advise all of its Assigned Risk client employers of the availability of the program.

c. Key elements that must be included in a Loss Management Program.

(1) The approved loss management firm must offer its qualified loss management program to every assigned risk client subscriber to its program wishing to avail itself of the credit assigned to the firm by The Workers' Compensation Rating and Inspection Bureau of Massachusetts

(2) The program must contain a provision stating that the credit applicable to the first year policy is subject to change on the second and third year policies.

(3) The program must contain a provision stating that a credit will not apply after the client employer has received a credit for four years.

(4) The program must contain a provision stating that a client employer must be involved in the program for six months before eligibility for the credit is established. If the client becomes credit eligible during the policy term, the credit is applied retroactive to the policy effective date; otherwise, the credit is applied on the effective date of the first policy renewal during which the client completes six months of participation in the program. The credit is pro-rated only when participation in the program terminates during the policy term, unless such termination occurs in the fourth annual policy period during which the client completes four years of participation in the program.

(5) The program must contain a provision stating that in the event of termination of the program by either the loss management firm, the client employer or The Workers' Compensation Rating and Inspection Bureau of Massachusetts, the credit shall be pro-rated.

3. Requirements To Apply For And Determination Of A Credit

The following requirements apply to a loss management firm submitting a Loss Management Program.

The method for determining the credit is as follows:

a. The loss management firm must submit data, in a format prescribed by The Workers' Compensation Rating and Inspection Bureau of Massachusetts, on all its client employers who have Massachusetts workers' compensation insurance premium and commenced the program within the last seven years. The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall have the right to inspect the books and business records of the loss management firm in order to verify that it is a complete list and accurately represents the experience of such client employers.

The data shall consist of copies of the experience rating modification calculations for the client employers. The object is to compare the experience for the year prior to the inception of the program to experience for the year subsequent to the inception of the program.

Example 1

Client starts Loss Management Program 7/1/85
Policy renews 7/1/85

Prior year's experience is for 7/1/84 to 6/30/85
Subsequent year's experience is for 7/1/85 to 6/30/86

Example 2

Client starts Loss Management Program 2/1/85
Policy renews 7/1/85
Prior year's experience is for 7/1/83 to 6/30/84
Subsequent year's experience is for 7/1/85 to 6/30/86

The required data is for the first report of the prior year and for the first report of the subsequent year. The Expected Losses, the Expected Primary Losses, the Actual Losses and the Actual Primary Losses for each of these two policy periods will be taken for each client employer. (The Massachusetts portion is used for interstate risks.) This information will be aggregated over all the client employers of the Loss Management Program.

This data covering the most recently available five-year period will be aggregated and then used to compute two experience modifications, one for the prior years and one for the subsequent years.

b. The qualification for a schedule rating credit is as follows:

Ratio of Experience Modification for Subsequent Years to that for Prior Years	First and Second Year Credit	Third Year Credit	Fourth Year Credit
0.807 or less	15%	7.5%	3.75%
More than 0.807 but at most 0.820	14%	7.0%	3.5%
More than 0.820 but at most 0.833	13%	6.5%	3.25%
More than 0.833 but at most 0.847	12%	6.0%	3.0%
More than 0.847 but at most 0.860	11%	5.5%	2.75%
More than 0.860 but at most 0.873	10%	5.0%	2.5%
More than 0.873 but at most 0.887	9%	4.5%	2.25%
More than 0.887 but at most 0.900	8%	4.0%	2.0%
More than 0.900 but at most 0.913	7%	3.5%	1.75%
More than 0.913 but at most 0.927	6%	3.0%	1.5%
More than 0.927 but at most 0.940	5%	2.5%	1.25%
More than 0.940 but at most 0.953	4%	2.0%	1.0%
More than 0.953 but at most 0.967	3%	1.5%	0.75%
More than 0.967 but at most 0.980	2%	1.0%	0.5%
More than 0.980 but at most 0.993	1%	0.5%	0.25%
More than 0.993	none	none	none

Each Loss Management Program must requalify for a credit annually.

c. Basis For Applying The Credit

If the Loss Management Program submitted by a loss management firm contains data on client employers with at least three governing classes, the credit will be applicable to all client employers in the program. Otherwise, the calculated credit shall apply only to hose client employers whose governing class is in the submitted data. For employers with other governing classes, the credit for newly established loss management firms shall apply unless the credit developed by submitted data is less than the credit for newly established firms whereupon such credit developed from the data shall apply.

d. The credit will apply to the Massachusetts portion of the workers' compensation premium (excluding expense constant) of the client employers in the program.

e. The credit shall not apply to client employers insured under a retrospective rating plan or a loss sensitive dividend plan.

f. A credit, as determined by The Workers' Compensation Rating and Inspection Bureau of Massachusetts, shall apply for four successive annual policy years to a client employer in good standing in the program starting with the first policy year of credit eligibility, subject to revision after the first and second years. The applicable credit is halved in the third policy year. The applicable credit is multiplied by 25% in the fourth policy year.

4. <u>New Loss Management Firms</u>

A newly established loss management firm may submit a Loss Management Program to The Workers' Compensation Inspection and Rating Bureau of Massachusetts for approval of a credit to apply to its subscriber client employers if:

a. The firm complies with the qualifications for loss management firms contained in Section 1.

b. The firm submits a Loss Management Program containing the key elements contained in Section 2.

c. The firm begins to submit the data required under Section 3 as soon as such data becomes available.

The credit for new loss management firms will be limited to 5% for risks in their first and second years, 2.5% for risks in their third year and 1.25% in their fourth year.

Three years after a new loss management firm as qualified, the credit for such a firm will begin to be based on its own data.

5. Administration Of A Loss Management Program By The Workers' Compensation Rating and Inspection Bureau of Massachusetts

   a. The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall be authorized by the Massachusetts division of Insurance to evaluate any Loss Management Program submitted by a loss management firm for purposes of offering client employers a credit, and shall issue a prompt notice of approval or disapproval.

      The factors that The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall consider in the evaluation of such a program are as follows:

      (1) qualifications of the loss management firm as listed in Section 1.

      (2) elements that must be included in submission of a Loss Management Program as listed in Section 2.

      (3) requirements to apply for an determination of a credit as listed in Section 3.

   b. If a Loss Management Program is not approved by The Workers' Compensation Rating and Inspection Bureau of Massachusetts, and the loss management firm making the submission is unsatisfied with the decision of The Workers' Compensation Rating and Inspection Bureau of Massachusetts, the loss management firm may appeal to the Commissioner of Insurance. Upon reviewing such an appeal, the Commissioner may, if he finds sufficient grounds for the appeal, call a public hearing to resolve the dispute.

   c. The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall be authorized to withdraw its approval of any loss management firm previously approved to offer a credit, if it determines, after a meeting with the firm, that the loss management firm is not in compliance with program requirements. In such case, the Bureau shall give the firm at least thirty days written notice that such approval is withdrawn and that its participation in the Qualified Loss Management Program is terminated. A copy of the required notice shall be sent to the Commissioner of Insurance at the same time that it is sent to the firm. Any action taken by the Bureau to withdraw approval my be appealed to the Commissioner of Insurance. Upon reviewing such an appeal, the Commissioner may, upon finding sufficient grounds for the appeal, call a public hearing to resolve the dispute.

      If the Commissioner has reason to believe that any loss management firm should be considered for removal from the credit plan, the Commissioner shall so inform The Workers' Compensation Rating and Inspection Bureau of Massachusetts. The Workers' Compensation Rating and Inspection Bureau of Massachusetts shall inform the Commissioner of what action, if any, it takes with respect to this Loss Management Program. If two months from the notification of The Workers' Compensation Rating and Inspection Bureau of Massachusetts, the Loss

Management Program still qualifies for the credit plan, the Commissioner may choose to call a public hearing to consider whether this Loss Management Program should be removed from the credit plan.

d. Each approved Qualified Loss Management Program must be resubmitted to The Workers' Compensation Rating and Inspection Bureau of Massachusetts annually, with updated data, for re-evaluation and calculation of a revised credit, if any.

U.S. Earthquake Frequency Estimation– Ratemaking for Unusual Events

Stuart B. Mathewson, FCAS, MAAA

U.S. Earthquake Frequency Estimation – Ratemaking for Unusual Events

By Stuart B. Mathewson, FCAS

Abstract

In our work on ratemaking, financial modeling, catastrophe modeling and planning, actuaries often must estimate the expected frequencies of unusual events. However, actual historical data for unusual events is too sparse to be very useful, so we must look to other sources for help. One example of these rare events is earthquakes. In recent years, the scientific community has performed significant research to better estimate the likehoods of earthquakes throughout the United States. Papers published by that community have presented much information that should be helpful in our quest to use earthquake frequencies in ratemaking, modeling and other actuarial work. This paper will present a basic discussion of scientific measures to estimate earthquake probabilities, a list of useful sources, and a discussion of several issues important to the understanding of earthquake ratemaking.

Introduction

Actuaries traditionally have had difficulty pricing coverages that have potential for large severity, but that have low frequency. Often, the prices charged for these coverages are determined by underwriting judgment and market forces, with little or no actuarial involvement. The catastrophe portions of property coverages are an obvious example of this situation. Among the insured catastrophe perils, earthquake is probably the most difficult to price.

Historically, pricing for the catastrophe portion of property rates has involved averaging losses over decades and large regions. However, changes in exposures and insurance coverages during those decades make traditional actuarial methods based on insurers' loss data very uncertain. The introduction of computer simulation models for estimating potential catastrophe losses now gives actuaries tools to help estimate catastrophe rates. For instance, the California Earthquake Authority, which writes a majority of the personal lines earthquake business in California, uses rates that were based on loss costs from computer simulation modeling. This type of model simulates losses from a large number of specific possible events. In order to convert these losses to loss costs, models take these simulated losses and apply frequency estimates to each event. These frequency estimates are critical, since any inaccuracy in frequency translates directly into inaccuracy in the loss costs.

The severity portion of an earthquake model carries significant uncertainty, but the frequency portion is probably more difficult to estimate accurately. There have been few historical events that have caused appreciable damage, and even fewer catastrophic earthquakes. Historical evidence is of limited use. Those responsible for ratemaking utilizing computer model output may believe that they don't need to know specifics about earthquake frequency since the estimates are imbedded in the models that they use. However, it is important to understand how frequencies are estimated because they are so critical to the rate that is indicated by the model.

This paper will describe some basics of how scientists estimate earthquake frequencies, where to look for frequency information and current issues on which experts disagree. The uncertainty of these estimates and the effect on ultimate rates will also be discussed.

Experts

If insurance loss data is confined to too short a time span to be useable, we need to find information elsewhere. The experts in earthquake frequency are seismologists and geologists. Seismologists study the historical earthquake records and the geological records. Geologists study the earth's crust to estimate how often the earth will move in certain areas. It is important to realize that 150-200 years is very short in the framework of geologic time. Thus, the geologic record of many thousands of years becomes paramount in estimating earthquake recurrence times.

We can look to published papers in professional journals, government publications and professional meeting presentations for the latest scientific research. Some of the sources for U. S. seismic frequency estimates are the Seismological Society of America (SSA), United States Geological Service (USGS), California Division of Mines and Geology (CDMG), Southern California Earthquake Center (SCEC), American Geophysical Union (AGU), and Earthquake Engineering Research Institute (EERI). Sources for earthquake frequencies outside of California include state geological surveys. Of course, universities provide much of the research underlying all the estimates. These groups are constantly providing new information to better understand the chance of earthquake occurrence.

Methods

Since estimating recurrence is so uncertain, scientists use a number of methods to arrive at their estimates. They measure the seismic slip of the earth's crust and the amount that slip that will be accounted for by an earthquake. They use statistical measures to extend the historical record to estimate likelihoods of very rare events. And, they use paleoseismic research to discover evidence of old earthquakes.

Seismic Slip Analysis

The earth's crust is comprised of tectonic plates that continually move with respect to one another. Where the plates meet, this movement is evidenced as strain in the crust. When the strain builds to a certain level, the crustal rock cannot hold it any more and it moves – earthquake! The amount of displacement resulting from this release of strain is known as seismic slip. Overall slip along a plate boundary can be estimated fairly accurately by modern measurement methods, so this method is useful for seismic areas at plate boundaries. Seismologists observe displacement of the ground in actual events, and can then estimate return times that accommodate the slip rate. The amount of slip is correlated to the amount of energy released by the earthquake, which is measured by the *magnitude* of the event. There are several types of magnitude definition, but for the purposes of this paper, we are using *Richter Magnitude* when we use the term.

A simplified example shows how this works. The San Andreas Fault is the boundary between the North American and Pacific plates in California. Along that fault, there is approximately two inches of plate movement per year. In the 1906 earthquake, there was up to 20 feet of displacement at various places along the fault. At two inches a year, it would take 120 years to build up enough slip to move that 20 feet. Thus, if

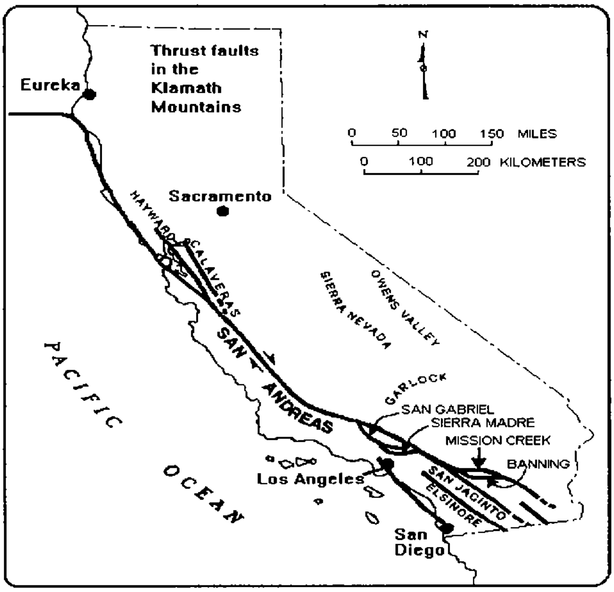


Figure 1

the San Andreas were a simple system that accommodated all the plate movement, the return time for this event could be estimated at about 120 years.

The real world, of course, is significantly more complex. Figure 1 shows the major faults in the San Andreas system in California. The faults are not simple lines, but a series of fractures, of which only a few are shown. There is significant work in apportioning the overall slip of two inches a year to individual faults, each capable of taking up some of the slip. For instance, in the above example, the San Andreas actually only accommodates about half the plate movement. In addition, there is the possibility of more than one fault segment breaking in the same event ("cascading event") and the fact that the release of strain in an event on one fault can change the strain in nearby parallel faults.

Gutenberg-Richter Relationship

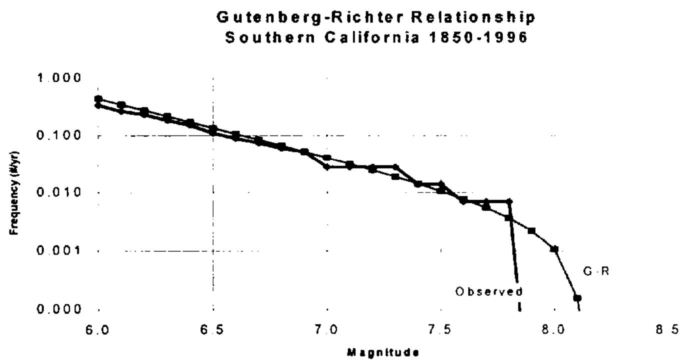
The rate of earthquake activity within a fairly large region can be estimated using a statistical approach, wherein the historical record of earthquake magnitudes and frequencies are fitted to a logarithmic equation. This equation is:

$$\text{Log } N = a - bM$$

In this equation, N is the number of earthquakes of magnitude equal or greater than magnitude M during a certain time period, while a and b are determined by fitting the equation to the historical record. Figure 2 shows an example of a curve for southern California.

This equation is used to estimate the likelihood of various earthquake magnitudes for an area, as well as to extend the historical record to magnitudes greater than historically observed. The use of the Gutenberg-Richter relationship is one of the areas of controversy among experts. The argument about the applicability of this relationship versus using a "characteristic earthquake" will be discussed later.

Figure 2



Paleoseismology

Since frequency of great earthquakes is often measured in terms of centuries and the U.S. historical record is less than 200 years, scientists have had to go beyond the record to discover how long the time is between the big shakes. Paleoseismology, the science of identifying and dating past earthquakes by examining the geological record, has proven to be very useful in extending our knowledge back from the historical record. There have been significant paleoseismic studies in most U.S. seismic areas, some of which are discussed below.

In one such study in Oregon, Nelson[7] and Bradley of the USGS studied soils buried beneath marshes. These soils show evidence of ground subsidence, much of which has probably been caused by major earthquakes. For instance, the 1700 earthquake discussed below probably caused significant subsidence. There have been 16 disturbances in the past 7,500 years, implying an average return time of about 500 years, assuming all the disturbances were caused by earthquakes. These, however, were not evenly spaced over the 7,500 years.

Up the coast in Washington, a similar study of buried soils showed one very large shallow earthquake about 1,000 years ago on a fault that runs directly beneath Seattle. Shallow earthquakes, less than 10 miles or so below the surface, can cause significant shaking, since there is less of the crust to absorb the energy released by the quake than from a deeper event.

The above work in Oregon and Washington is very important, since the Pacific Northwest has the chance for a great subduction earthquake. That is, an earthquake where one fault pushes under another and which can generate earthquakes of 9.0 magnitude or greater. The Juan de Fuca plate moving eastward beneath the North American plate along the coast of Oregon, Washington and a portion of British Columbia would cause this earthquake. Native American lore in that area told of a great earthquake about 300 years ago. An earthquake of that size and type would have almost certainly caused a major tsunami (seismic sea wave) that would have proceeded across the Pacific. Accordingly, Japanese records were searched and, as expected, there was a record of a tsunami in January 1700. From those records, scientists have calculated that a great subduction event happened off the Pacific Northwest coast on January 27, 1700.

Juan de Fuca Plate

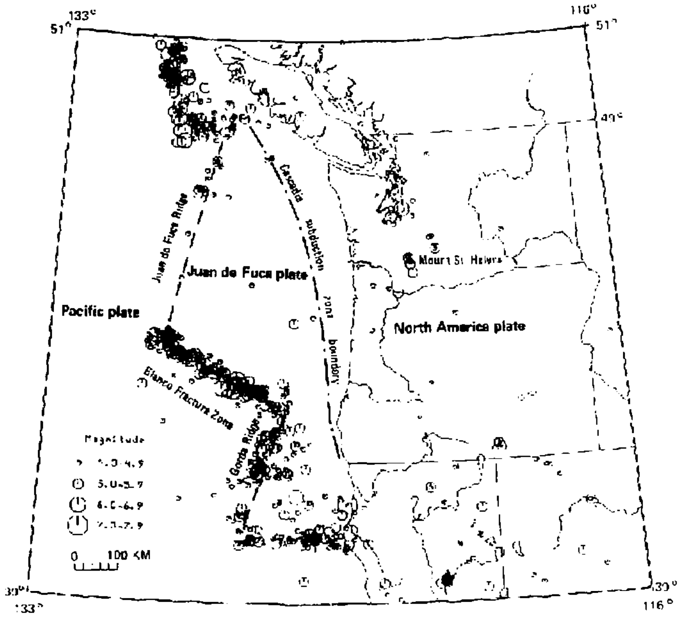


Figure 3

In the New Madrid seismic area of the Central U.S., there has been great concern about a large earthquake. This area suffered a series of great earthquakes (magnitudes over 8.0) in 1811-1812, but there is very little historically to help us estimate the return time of such an event. To investigate the area, paleoseismologists such as Buddy Schwieg[16] of the USGS and Steve Wesnousky[17] of

Nevada-Reno have dug trenches in the affected areas. The walls of the trenches were then studied to see evidence of past earthquakes.

In the 1811-12 earthquakes, there was significant liquefaction of the soil. This is a condition where the earthquake mixes sandy soil and water to create a fluid soil. This condition is often evidenced as sand blows, fluid sand shooting up to the surface, looking like large anthills. In the trenches, there was evidence of sand blows that have been carbon-dated at approximately 900 and 1300 A.D, with two others in the past 2,000 years. This would imply a return time of about 500 years for events large enough to cause sand blows. Some of these may not have been quite as large as the 1811-12 events, although one may have been larger. Thus, scientists have estimated that events of over 8.0 probably have return times of between 400 and 1,100 years. There are a couple of items that show the difficulty in this type of estimation. First, studies of different fault segments show different areas of liquefaction at different times. In addition, Schweig and others have shown evidence of another earthquake between 1400 and 1600 A.D.

There has also been significant trenching activity in Southern California. One very interesting finding arose after the magnitude 7.3 Landers earthquake of 1992, east of San Bernadino, which was an event that ruptured multiple faults. Kerry Sieh[13] of Cal Tech, discovered through trenching that some of these faults had not broken for over 10,000 years, so, of course, would have no historical record.

Sieh also has done work in the southern San Andreas Fault system (Pallet Creek) that shows an additional source of uncertainty in likelihood estimation. In that area he showed ten precisely dated earthquakes over the past 2,000 years. However, they were not evenly spaced over that time. There were four clusters of two or three events each preceded by periods of dormancy that lasted two to three hundred years. Each cluster happened within a one hundred-year period. Thus, the long-term recurrence for these events is about 200 years, but the time between specific events could be much lower. Similar studies have indicated that clustering has occurred in other locations, and is common. Thus, even when scientists can identify the average recurrence time of an earthquake on a fault segment, the actual time between events can vary significantly.

These are samples of paleoseismic research that have provided very helpful information. From this information, we have much better estimates of probabilities of very large events than available from history, but we are also aware of the difficulties involved in the process, and the uncertainties introduced in the frequency estimates.

Sources of Frequency Information

There are several publicly available sources of frequency estimates. Of course, given the seismicity of California, that area has received the majority of the attention.

U.S.G.S. Open-File Report 88-398[19]

In 1988, the USGS published a study of the frequencies of California earthquakes, covering the major strike-slip faults of the San Andreas fault system. The work was done by a group of academics and other scientists known as the Working Group on California Earthquake Probabilities. The study, USGS Open-File Report 88-398, produced probabilities for three major seismic areas, the San Francisco Bay area, the Southern San Andreas Fault and the San Jacinto fault. In order to help the public understand them, the likelihoods were expressed in terms of the probability of a certain magnitude event over the next thirty years. The 1988 probabilities are summarized in the table below. Both the 30-year and annual probabilities are shown.

Table 1

Geographic Region of Fault	Expected Magnitude	Probability of Occurrence in 30 Years	Annual Probability
San Francisco Bay Area	7.0	50%	2.3%
Southern San Andreas Fault	7.5-8.0	60%	3.0%
San Jacinto Fault	6.5-7.0	50%	2.3%

U.S.G.S. Circular 1053[18]

The 1989 Loma Prieta earthquake on the San Andreas Fault south of San Francisco precipitated a new look at the 1988 work. In 1990, the Working Group revised its estimates for the San Francisco Bay Region, covering the North San Andreas Fault and the Hayward Fault in the East Bay. This was published in USGS Circular 1053. In addition to reflecting the change in stress after the Loma Prieta event, the Working Group also considered faster fault-slip rate estimates and included the Rogers Creek Fault, the northern extension of the Hayward Fault. The changes in probabilities are shown in the following table.

Table 2

Fault Segment	Expected Magnitude	30 Year Prob 1988	Annual Prob 1988	30 Year Prob 1990	Annual Prob 1990
San Andreas - N	7.0	20%	0.7%	23%	0.9%
Hayward North	7.0	20%	0.7%	28%	1.1%
Hayward South	7.0	20%	0.7%	23%	0.9%
Rodgers Creek	7.0	NA	NA	22%	0:8%
Total S. F. Bay Area		50%	2.3%	67%	3.6%

This is a rather significant increase over the 1988 estimate; even excluding the Rodgers Creek Fault brings the 1990 estimate for the area to about 60%, a 20% increase.

SCEC Study[20]

The 1994 Northridge earthquake sparked another revision to the 1988 report, this time for Southern California. The Southern California Earthquake Center coordinated a new study by the Working Group that updated the Southern California probabilities from the 1988 study (for the San Andreas and San Jacinto faults) and also considered other potentially damaging earthquakes in that region. The study was published in the April, 1995 issue of the *Bulletin of the Seismological Society of America (BSSA).*

The modeling was considerably more complex and included the entire Southern California region. The models predicted a 30-year probability for a magnitude 7 or larger event of between 80% and 90%. Because of the differences in methodologies, this study is hard to compare to the 1988 estimates, but it definitely increased the perception of the earthquake problem in Southern California. The SCEC study added several fault segments, included provision for "blind thrust-fault" earthquakes (those that do not break the surface, for example, Northridge) and revised some slip rates upwards. They also produced a method to include the chance of more than one fault segment breaking in a single event (known as "cascading earthquakes"). The 1992 Landers and the 1857 Ft. Tejon earthquakes were examples of this type of event, so this method should help provide more realistic estimates of return periods for large events.

However, there has been some controversy about this study. When the predicted probabilities are compared to the historical record, they exceed the historical earthquake. The current discussions of that anomaly will be discussed later.

USGS Hazard Maps

In 1997, the USGS and the CDMG published new hazard maps for the U.S., showing levels of ground shaking at specified exceedance probabilities throughout the country. While these are not strictly frequency studies, these maps combine frequency and severity, and as such, are good for comparing overall hazard to other sources.

Non-California Sources

While this paper has concentrated on California probability sources, the potential loss from earthquakes in other areas of the country is certainly important, and so are their likelihoods. Other areas include the New Madrid seismic area, the Pacific Northwest, Charleston, S. C., and Salt Lake City. Some sources for these areas, in addition to the paleoseismic work above, are listed in the References section.

Ratemaking Effects

Loss costs underlying earthquake rates can be quite sensitive to the model frequency estimates of the largest, most rare events. For instance, assume experts believe that the return time for a magnitude 8 or greater event in the New Madrid seismic zone is between 500 and 1,000 years. This size event would be considerably more damaging than lesser events in a library of potential events in a model, so the choice of frequency could have a significant effect on the total loss costs for that seismic zone. As a simplistic example, see Table 3 on the next page. If the frequency of the worst event in that table were doubled, the overall loss cost would rise from $7 to 10 million.

Current Controversies

Although seismologists have developed many very useful methodologies to improve their earthquake probability estimates, there is still much uncertainty. There are disagreements among the scientists about the best estimation methods. A few of the current issues will be discussed to show the extent of the uncertainties.

Gutenberg-Richter vs. Characteristic Earthquakes

Earlier, the Gutenberg-Richter relationship was explained. While most will agree that this is a useful concept, there is disagreement over when it should be used. For a specific fault segment, many scientists believe that there will only be one certain size event, known as a "characteristic" earthquake. They believe that strain will build to a certain point, and then the fault will break. The amount of slip will be essentially the same each time, and will result in a similar fault rupture and, thus, a similar magnitude earthquake. For that fault, Gutenberg-Richter would not apply, since there wouldn't be a distribution of possible magnitudes. If this is true for all individual fault segments, then Gutenberg-Richter is only a valid concept for a region of such faults. The question is, "How big must a region be for the relationship to be valid?"

This is a very important question for earthquake modeling, since assuming a distribution of several possible magnitudes on a large number of faults may give different answers than a distribution that assumes only one potential magnitude per fault. It is typical for earthquake loss models to simulate several different magnitude events on each fault segment, giving decreasing probabilities to increasing magnitudes. If only one magnitude can happen, the distribution of probabilities by magnitude for a library of events will be different.

In a simplistic case, we have assumed that the characteristic earthquake for a certain fault is a 7.0, and a Guttenberg-Richter relationship shows the possibility of damaging quakes from 6.0 to 7.5. We have also assumed that the losses for various size events follow the pattern in the table below. The table shows potential losses with assumed frequencies and losses for the spectrum of events where the total annual frequency is 0.15 events per year.

Table 3

Magnitude	Annual Frequency	Loss ($Millions)
6.0	.08	10
6.5	.04	30
7.0	.02	100
7.5	.01	300
Annual Total	.15	7

If the characteristic event of 7.0 were the only event to occur, the frequency of that event would be 0.15. Thus, the annual average loss would be 0.15 x $100, or $15 million, more than twice that of the Gutenberg-Richter assumption. While this is a simplistic example, differences like this can occur for a number of seismic areas, so that this difference in opinion can potentially have a large overall effect.

The Paradox

In the August 1997 issue of the *BSSA*, Didier Sornette and Leon Knopoff[14] published a paper called, "The Paradox of the Expected Time until the Next Earthquake." The authors address the question; "Can it be that the longer it has been since the last earthquake, the *longer* the expected time till the next?" This is in opposition to the conventional wisdom says that, as the time since the last event increases, the probability of the next occurrence increases. The common assumption is that strain is released in an event, and then begins building up until it reaches a point that the earth gives way again. This seems intuitively correct, but the authors argue that this is not always the case. This is important for ratemaking, since the frequencies used in the models often use the best estimate of the near-term frequency, rather than the long-term frequency for an event. For example, if the long-term return time for a certain earthquake is 100 years (frequency of 0.01), but it has been 75 years since the last event of that type, the frequency used will be much higher than 0.01.

Their analysis suggests that the answer to this question depends on the inherent statistical distributions of the fluctuations in the interval times between earthquakes. Several distributions, including the periodic, uniform, semi-Gaussian and the Weibull (with exponent greater than 1), all have a *decreasing* return times with the passage of time since the last event, as we would expect. However, the lognormal, power law and Weibull with exponents less the 1 have *increasing* return times.

One explanation for this possibility is found in examining clusters of past earthquakes. If we believe that earthquakes in an area behave in a clustering fashion, we can expect a repeat of an event relatively shortly after an event that follows a long dormancy. But, as the time following that event gets longer, we might believe that we are in another long dormant time, rather than a time between clustered events.

In ratemaking, this means that the uncertainty of these events is increased. Not only do we have to estimate the long-term frequency, with its uncertainty, but we also have to factor in the effect of the time since the last event, and whether this increases or decreases the frequency used in the ratemaking process for the next year.

The Enigma in the SCEC Report

As mentioned earlier, since the release of the SCEC report, seismologists have hotly discussed the reasons why the estimates significantly exceed those implied by the historical record. The graph in figure 4 shows the difference. The top line is the predicted frequency, while the bottom is the historical record. Since this is a on logarithmic scale, the prediction is actually about twice that of history in the magnitude 6.0 to 7.0 range, where we find many damaging events.

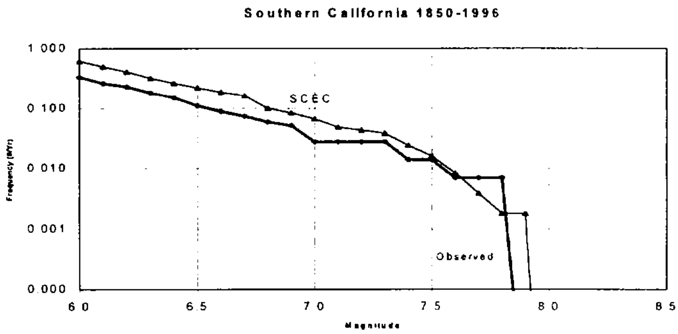


Figure 4

Three possible reasons have been put forth to explain this difference. First, slip has been taken up aseismically; that is, there has been slow movement of the earth without earthquakes ("creep") and folding of the crust. Secondly, we may have been "lucky" over the past 150 years, or so. That is, the actual frequency has been significantly lower than the long-term frequency for the area. Thirdly, there is the possibility of an event much larger than the historical maximum, which was a Richter magnitude of about 8.1. This may or may not be a significant problem, depending on the accuracy of the historical record. That is, small changes in the magnitude estimates of older historical events could account for much of the difference. The report itself addressed this, suggesting that earthquake activity in the region for magnitude 7 and greater earthquakes has be anomalously low since 1850, although there was one great earthquake. Just one additional great earthquake would erase the difference. This is one example of the sensitivity of earthquake frequency estimates.

David Jackson of SCEC has been addressing this enigma with the following theory. There seems to be no evidence that any significant creep has occurred in the area, and, we can theorize that the 150-year period is long enough to show a reasonably accurate estimate of long-term occurrence rates for medium earthquakes (magnitude 6-7), where the difference is greatest. Thus, Dr. Jackson has felt that the most likely answer was that a much larger event could occur than the largest historical quake, the 1857 Ft. Tejon event. This "mega-earthquake" needs only to have a return time of about 1,000 years to take up the excess slip that is unaccounted for.

However, during the March 1998 annual meeting of the SSA, two teams of researchers disputed the necessity for a "mega-earthquake." SCEC has further reviewed its study and found a number of small flaws that combined to overestimate the estimate of the amount of slip building up in Southern California. They have revised the model such that the difference between historical and theory has virtually disappeared. At the same meeting, USGS scientists questioned the historical list of magnitude 6 and greater events that was used by SCEC. They argue that the list may have ignored quakes that occurred early in the time period, when inland California was relatively unpopulated. They point out that the observed earthquake rate since 1903 is almost 50% greater than that recorded since 1850. If there were an appropriately higher early rate, the SCEC difference would be reduced. This may or not be the case, since 150 years of earthquake history is so short compared to geologic time. (Note that the earthquake rate in the San Francisco area was very high in the 70 years prior to 1906, and has been very low since.)

The answer to this enigma can certainly effect the loss costs that are modeled in Southern California. If the "true" relationship includes about half the moderate earthquakes that are currently reflected in a model, but has a very rare large one that is not now reflected, "true" loss costs will certainly be different, although it is difficult to estimate whether they would be higher or lower.

Conclusion

Now that scientifically based catastrophe modeling is being used to support earthquake insurance rating, we must be aware of the importance of the probabilities used and the uncertainty in those probabilities. The scientific community, led by the USGS, CDMG and SCEC in California, continues to research the area to give us better information. This research will continue to progress, and we can expect the estimates to evolve. However, the significant disagreements among the scientists, even in California, highlight the uncertainty involved.

We as ratemakers must be aware of the assumptions underlying the rates. When loss costs are based on computer models, the frequency assumptions are often buried in the models. We need to know the sensitivity of the estimates so we can understand the uncertainty of the rates, and make informed pricing decisions.

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Implications of Dynamic Financial Analysis on Demutualization

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Introduction

Recent announcements such as the Prudential's plan to fully demutualize have brought the issue of demutualization to the forefront of the insurance industry. The Center for Insurance Research estimates that one in six households may be impacted by the demutualization of Prudential alone. A number of other mutuals have also discussed plans to demutualize or are currently in the process of demutualizing: John Hancock, Standard Life, General American Life, Pacific Life, Mercer Mutual, Metropolitan Life, Mutual Life, and Farmers Casualty Company Mutual, to list a few. UNUM, Equitable, Reliastar and Allmerica represent a few of the growing number of companies that have successfully demutualized over the last decade.

Based on A.M. Best's Aggregates and Averages as of December 31, 1996, 396 Property & Casualty (P&C) mutuals have over $205 billion in cash and invested assets, with an additional $25 billion in non-invested assets. They are currently holding loss and loss adjustment reserves of $93 billion and unearned premium reserves of $33 billion. Total consolidated policyholder surplus for the mutual companies reviewed by A.M. Best exceeds $82 billion dollars as of December 31, 1996 [1].

The aforementioned figures emphasize the importance of demutualization analyses for the P&C industry. Although most of the activity has occurred on the Life side, the P&C industry is now witnessing a similar increase in demutualization activity driven by the need to access additional capital. Not only are the amounts of dollars at stake staggering, demutualization also has a number of direct and indirect impacts:

- Direct impact on current policyholders' ownership rights;
- Direct impact on company management incentives and compensation (i.e. stock options);
- Direct impact on government legislation and statutes that control the authorization and regulation of P&C demutualizations;

- Direct impact on competitiveness of the insurance market and access to capital;
- Direct impact on the supply and demand of stock insurance companies listed on the NYSE and NASDAQ;
- Indirect impact on the market value of current stockholder owned companies as investment advisors reassess current market valuations based upon alternative investment options; and
- Indirect impact on the legislative agendas in other states that have yet to approve statutes and legislation governing demutualizations.

The authors currently use DFA to focus on four key target markets within the insurance industry:

1. Analysis of risk through future time horizons with implications on strategic planning, operations, investments and surplus allocation;

2. Actuarial appraisal of economic value for P&C insurance company demutualizations;

3. Review of an individual client's reinsurance program and opportunities for enhancing coverage in a more cost effective manner; and

4. Traditional reviews of cash flow and capital adequacy.

The purpose of this paper is to describe and explain how the new and evolving field of dynamic financial analysis (DFA) can be used in the assessment of P&C mutual insurance company demutualizations and the actuarial appraisal of economic value.

Demutualization Feasibility

Industry analysts and companies in the process of demutualizing who have posted information on their web sites say the number one answer to the question "why demutualize?" is "access to capital". John Hancock's web site http://www.johnhancock.com answers the previous question by stating:

> "*The financial services marketplace has changed dramatically. Competition has become extreme and consolidation rapid. To compete successfully, mutual insurance companies across the country have recognized the need to access unprecedented amounts of capital to invest in new products, agency and other distribution channels, improved customer service and technology. In an industry that has seen tremendous consolidation recently, large amounts of capital are also needed to undertake strategic acquisitions or alliances to compete with new insurance providers as well as larger financial services firms which are taking shape today through consolidation.*"

The Bowes Funds web site http://www.bowesfunds.com answers the question:

> "*Access to Capital. As a result of government deregulation, banks and insurance companies are now able to conduct business in expanded geographic areas and offer a broader range of product lines. To take advantage of this added flexibility, many of these companies need to raise additional capital to expand their operations and implement technological upgrades; however, mutually owned banking and insurance companies are limited in their access to capital by the size of their accounts. Converting to public ownership allows these companies to raise the capital they need through the sale of shares to accountholders and outside parties.*"

The next logical question to ask is why mutual companies cannot raise capital under their current structure. The white paper draft titled Mutual Insurance Holding Company Reorganizations from the National Association of Insurance Commissioners (NAIC) lists four ways a mutual company can increase their capital base:

1. Through retention of net profits;

2. Issuance of surplus and capital notes;

3. Offering shares of stock in a downstream subsidiary, and

4. Merger.

Expansion into different geographic areas or entering new lines of business requires a large amount of initial capital investment. The above methods are not efficient alternatives for achieving growth, profitability and responding to market opportunities. Retention of net profits is largely driven by the current hardness or softness of insurance prices. A company's current line of business profitability depends upon the market prices underlying each book of business. Increasing profitability generally requires a combination of raising policyholder premiums, writing more profitable accounts, reducing losses, or reducing expenses such as agent commissions and acquisition expenses. Since companies are already heavily focused on minimizing costs and expenses and developing profitable books of business, obtaining the capital through current profits to finance new growth is difficult at best.

The issuance of surplus and capital notes has a number of drawbacks. The white paper draft from the NAIC lists a number of limitations for using surplus notes:

- A surplus note is a form of debt that must be repaid, therefore, no permanent capital is created;
- A number of states have imposed limits on the total amount of policyholders' surplus that can be derived from the issuance of surplus notes;
- Surplus notes, as a form of capital, carry a substantial cost in the form of debt service;
- Surplus notes require regulatory approval of all payments of principal and interest. This creates uncertainty for an investor, raising the cost of capital; and
- Insurance rating agencies typically count surplus notes as debt, i.e. a liability, rather than equity, in their evaluation of an insurance company's claims paying ability.

Capital notes have similar drawbacks to surplus notes as discussed above, except interest and principal repayments often do not require the approval of the insurance regulator.

Offering shares of stock in a downstream subsidiary has a number of operational and regulatory limitations, the most significant of which eliminates the use by the parent of the newly raised capital from the subsidiary stock offering. All capital raised must remain in the new stock subsidiary, resulting in no direct benefit to the parent company since capital cannot be reallocated where needed within the organization.

Mutual companies may also choose to merge with other mutual insurance companies. Unfortunately, merging with other mutual companies does not address the need for additional capital. Although reductions in duplicate staff and the consolidation of financial, marketing, operational, and other areas may reduce expenses, the merged company still must address the issue of increasing capital through retention of the combined entity's net profits.

Demutualization Process

The demutualization process requires a number of different phases in order to transform a mutual company into a stockholder owned company. A diagram of the five phases has been attached in Appendix A. The paper focuses on phases two through four but a brief description of phases one and five has been included below.

The first phase requires company management to decide whether or not they need to demutualize in order to access additional capital. Management's need for additional capital can be driven by a number of factors such as investment in and implementation of new technology, rapid growth of existing lines of business, expansion into new lines of business and strategic acquisitions or mergers. The insurance industry has seen tremendous consolidation with mega mergers like Citibank and Travelers as well as Berkshire Hathaway's proposed purchase of General Reinsurance. The aforementioned transactions as well as a host of other deals occurring throughout the P&C industry have increased competition across all lines of business. Mutual companies are now competing against enormous financial institutions with widening distribution channels through the use of banks and affinity relationships. An opportunity to level the playing field for most mutual companies lies in the ability to access additional capital through the capital markets and the initial public offering process by choosing to demutualize.

The second phase requires the completion of a number of different tasks in order to perform the DFA analysis. The first task requires an in-depth review of historical company data and discussions with company management. The review focuses on all aspects of the balance sheet, the income statement and the cash flows generated by the company. A number of the key assumptions underlying the model such as expected loss ratios, investment returns, asset classes and expense ratios can be established at this time. The second task involves the mock-up and parameterization of the stochastic model. A thorough review of the underwriting module, payout module and investment module occur at this time as well as the customization of the model for any company specific assumptions. The third task requires a review of the model with the stochastic switch turned off. It is important to verify the expected results generated by the model for reasonability and consistency with historical results achieved by the company. The model outputs a number of operating ratios and leverage ratios that can be compared with the historical ratios produced by the company.

The third phase establishes the actuarial appraisal range of value by stochastically simulating company results for the future years. Each individual simulation is saved in the storage module for use in the confidence interval testing. The authors currently use a middle eighty percent confidence interval to establish the actuarial appraisal range of value for the mutual company under review. The appraisal value factors used in determining the actuarial appraisal range of value are derived using the ratio of the estimated company value simulated by the model to the company's actual December 31st surplus for the last historical year.

The fourth phase requires the acceptance of the results by management, the insurance department and the policyholders. This phase initially involves in-depth discussions between company management, legal representatives and the insurance department about the underlying assumptions and appraisal range determined by the model. It is important to communicate what the appraisal range of value does and does not cover. For example, the model does not estimate the purchase price that would be agreed upon between a potential buyer and seller. Items such as the perceived value in the company's name brand recognition, agency distribution network, value of licenses, and goodwill are not explicitly included in the model's appraisal value. Although some of the items may be implicitly included in the appraisal value, they may require a subjective analysis by company management in order to determine the final compensation value that will represent the policyholders' ownership interest in the company.

The fairness of the final compensation value determined by management and adopted by the Board of Directors is discussed at a public hearing called by the Commissioner of Insurance from the company's state of domicile. The purpose of the public hearing is to review the policyholder notice issued by the mutual company and to discuss any issues that arise about the determination of the final compensation value. The key goal of the public hearing is to determine whether the mutual company's plan for converting to a stock company is fair and equitable to the policyholders.

The fifth phase deals with the company's next steps after completing the demutualization and becoming a stock insurance company. As the company acquires additional capital and begins entering into new lines of business, growing existing lines of business, acquiring companies, or merging, it is important to analyze the proper allocation of surplus to the investments opportunities that will generate the highest returns with the lowest amount of risk. This type of analysis requires a more sophisticated DFA model addressing issues such as analysis of reinsurance on a contract by contract basis using a frequency-severity based approach, implementation of management intervention steps (e.g. reserve strengthening and portfolio rebalancing), and impacts on the company's ratings.

Demutualization Methodology

The authors determine an actuarial appraisal range of value based upon the application of a DFA model which estimates future statutory income, cash flow, and dividends to policyholders (or capital contributions) with supporting balance sheets, income statements and cash flow statements. The dividends determined by the DFA model represent payments from statutory earnings that could be made, subject to constraints in assumed leverage based on maintaining either a net liability to surplus ratio or a net written premium to surplus ratio. If earnings are not sufficient to allow a dividend payment, the DFA model provides for a capital contribution. The actuarial appraisal value for current policyholders is estimated by taking the present value of estimated future policyholder dividends (or capital contributions), plus the remaining surplus at the end of the simulation period, discounted at the opportunity cost of capital (OCC). The actuarial appraisal value can be adjusted for two additional items, including the tax implications associated with the adjustments:

1. Inadequacy or redundancy in the stated reserves; and

2. Adjustment of assets to their fair market value.

The DFA model utilizing the above methodology was actually developed using a more complex DFA model which was developed by the authors' firm for individual insurance company strategic planning, management review and intervention, and surplus allocation. Some of the features of the larger model such as surplus allocation by business unit or line of business, investment portfolio turnover and rebalancing, management review and intervention, and the development of reinsurance on a contract-by-contract basis, are not needed for the estimation of a mutual company's actuarial appraisal of economic value. The authors nicknamed the DFA model "DFA-Light" due to its ease of use and manageable size. The simplified DFA model has a number of advantages:

- The model is very customizable and easy to use since it is in spreadsheet form;
- Mutual company annual statement data is readily available and easy to load into the model;
- The model is easier to parameterize than the larger DFA model;
- The key assumptions underlying the model and the simulation results and graphical output are easy to explain; and
- The analysis can be completed in a relatively short period of time, as compared to the time required by the more sophisticated, larger model.

Appendix B displays a flow chart of the model.

Conceptual Framework

To understand the conceptual framework behind the establishment of the actuarial appraisal range of value and the determination of the OCC, we have decided to take a step back and provide a simplified example. The example below will help to explain some of the more counterintuitive results that can be derived using the DFA model.

Suppose an investor has \$747.26 to invest. The investor is presented with two investment options:

1. Purchase a risk-free five year zero coupon bond, with a 6.0% yield; or

2. Invest in XYZ Casualty Mutual.

XYZ Casualty Mutual's premiums are written and earned on 12/31/XX, losses are incurred and paid on 12/31/XX, the company pays no taxes or investment expenses, invests in one year bonds with a 6.0% coupon, and writes business at a 1:1 premium to beginning surplus ratio. However, insurance results are uncertain and likely to vary from the expected level. For purposes of this example XYZ Casualty Mutual is assumed to have a 30% probability of running a 100.0% combined ratio (CR) (see Appendix C.1), a 19% probability of running a 90.0% CR (see Appendix C.2), and a 51% probability of running a 105.0% CR (see Appendix C.3).

If the investor chooses the first option, the \$747.26 investment grows with certainty to \$1000.00 (\$747.26 x $(1.06)^5$) at the end of five years. If the investor chooses the second option, the expected return is the same \$1000.00 at the end of five years based upon the probabilities specified above (see Table 1). Although the investor expects to earn 6.0% annually, the investor has a 51% chance of earning 1.0%, a 30% chance of earning 6.0%, with only a 19% probability of earning in excess of the 6.0% return at 16.0%.

In order for the investor to choose the second option, the investor must be compensated for assuming the additional risk by receiving a higher return on his/her investment. This higher return is the investor's OCC. The OCC is itself dependent on the investor's expectations of future interest rates, inflation, the risk represented by the volatility of earnings in the insurance business and the perceived prospective returns from alternative investment options available to the investor.

Assuming other insurance companies writing similar lines of business return 10.0% to their owners, the investor could set his/her OCC at 10.0%. The 4.0% return above the 6.0% risk free rate represents the investor's perceived cost of assuming the additional underwriting risk. Table 1 summarizes the results:

Table 1

	Probability	Initial Investment/ Beginning Surplus	12/31/02 Return	Annual Percent Return	OCC	OCC Adjusted Return	Ratio to Initial Investment
OPTION 1							
Zero Coupon Bond	100%	747.26	1000.00	6.0%	6.0%	747.26	1.000
OPTION 2							
XYZ Mutual	100%	747.26	1000.00	6.0%	10.0%	620.92	0.831
CR - 100.0%	30%		1,000.00	6.0%		620.92	
CR - 90.0%	19%		1,569.50	16.0%		974.53	
CR - 105.0%	51%		785.38	1.0%		487.66	

Using risk adjusted returns, the investor can now see that investing in the zero coupon bond and investing in XYZ Mutual with an expected $1000 return is not equivalent. The investor could have taken the $747.26 and invested in a higher yielding corporate bond or invested in another insurance company which offered higher returns commensurate with the amount of risk taken on by the investor.

The above example helps to demonstrate how the company's growth from the current surplus level can actually be eroded over a number of years when compared to the risk-free investment. If XYZ Mutual's investment strategies are below average or the company runs combined ratios in excess of industry norms, the company will continue to increase surplus, but at a rate well below the desired OCC. This helps to explain why a portion of the actuarial appraisal range is below the beginning surplus for some of our demutualization analyses. Even a company with sound investment strategies and competitive combined ratios can produce results below the starting surplus when the stochastic simulation produces larger losses than normal or poorer investment returns than expected for some of the individual simulations.

Parameterization

Parameterization of the DFA model requires extensive initial discussions with the company's management and a review of their statutory annual statements for the last three to five years. The report underlying the statement of actuarial opinion and a review of the auditor's independent report help in reviewing the actual historical results of the company for use in model simulation.

As discussed previously in the section titled **Demutualization Process**, the second phase involves a thorough review of the data requirements for the underwriting module, payout module and investment module. Although historical company data derived from internal company reports, the statutory annual statement and other workpapers are extremely valuable, these data sources are inadequate to fully parameterize the model on a stand alone basis. A variety of external data sources can be used to assist in the evaluation of the company's data in order to parameterize the model.

The parameterization of the investment module involves the determination of expected returns, variation and correlation by asset class. Depending on the complexity of the mutual company's investment strategy, internal historical data may be inadequate to properly parameterize the model. A valuable external source for key U.S. asset class data is Ibbotson's "Stocks, Bonds, Bills, and Inflation Yearbook" which provides total returns and index values for stocks, long-term bonds, long and intermediate term government bonds and treasury bills. The necessary items can be loaded into the model based upon the asset class allocation of the mutual company under review. As with all assumptions utilized in the model, the simulated before-tax portfolio yield must be compared with historical company results in order to verify the reasonability of the selected asset class parameters.

The parameterization of the payout module involves the estimation of line of business payout patterns and the loading of tax specific information under §846 of the Internal Revenue

Code. The selection of the line of business payout patterns is largely dependent upon the amount of available company data. In situations where the company's historical data lacks the credibility to sufficiently estimate a reasonable payout pattern for a line of business, industry data can be credibility weighted with the company's data in order to select the appropriate payout pattern. A number of industry sources exist for reference such as Sheshunoff's loss reserve development patterns for primary and reinsurance companies, Reinsurance Association of America's (RAA) loss development factors, and A.M. Bests Aggregates & Averages Property-Casualty review.

It is important to note that the size of the DFA model is largely dependent upon the number of lines of business written by the company and how investible assets are allocated in the company's portfolio between taxable bonds, tax-exempt bonds, stocks and other available asset classes. A number of other items can impact the size of the model but to a much smaller extent. Other income items such as finance and service charges from installment plans, treatment of non-investible assets, smaller scale liability items, and the handling of deferred compensation benefits and post-retirement health benefits can increase the model's size. As one would expect, the larger the mutual company, the more complicated the analysis becomes. The initial discussions with management and financial documents discussed above help to set the framework for the final layout of the DFA model.

Key Assumptions

Two of the key assumptions to determine the actuarial appraisal range of value in the authors' DFA model are:

1. Leverage Ratio

2. Renewal Retention Ratio (RRR)

The DFA model allows the user to select either a net liability to surplus ratio or a net written premium to surplus ratio to control the indicated dividends required from the policyholder. To the extent that net earnings in future years are not sufficient to maintain the selected leverage ratio, a capital contribution is indicated. Otherwise, a dividend to policyholders is reflected to bring the ratio to the selected leverage ratio. The leverage ratios can be derived from industry comparisons with companies writing similar lines of business or based on an individual state's regulatory requirements. Selection of the appropriate leverage ratio should reflect many risk factors including uncertainty in underwriting financial results, cash flows and investment returns.

A leverage ratio is applied to maintain a uniform risk profile over the simulation period. Essentially, dividend and capital contributions are controlled in such a way as to maintain a balance between the insurance liabilities and the capital supporting them. In this process, consideration is given to factors that impact both liabilities and surplus, including those reported under conventional accounting and the economic adjustments mentioned previously.

The RRR represents the percentage of policyholders that renew each year and is easily derived from historical company data. Our model applies the RRR to the company's in-force business, resulting in a run-off of the current policyholders net written premium over the ten year simulation period. The method can be classified as a "run-off" approach since we do not consider the value of future business that could be generated by the company. The "run-off" approach was selected over an approach that also considers the value of future business generation due to the policyholder's unique ownership interest in a mutual company. Unlike a stock insurance company where the owners' value (shares outstanding) is fixed regardless of the growth in the number of policyholders, a mutual insurance company owners' value is diluted as the number of policyholders grows, since each additional policyholder becomes an owner of the company. Using the RRR "run-off" approach provides an estimate of the actuarial appraisal value without diluting the current policyholders' ownership interest.

Losses and Reinsurance

The authors have used two approaches when modeling losses and reinsurance:

1. Net ultimate expected loss ratio (ELR) approach

2. Frequency and severity (FS) approach and the modeling of reinsurance on a contract-by-contract basis

We currently use an ELR approach for the estimation of ultimate loss and allocated loss adjustment expense (ALAE) by accident year. The ELR can be compiled directly from historical company results since the actuarial report and internal company reports often provide ten or more years of net ultimate loss ratios by line of business. The mean and the standard deviation can be determined explicitly for each line of business. Table 2 shows an example of how to calculate the mean and standard deviation using XYZ Mutual's ultimate accident year loss ratios for the last nine years. The expected loss ratio and the standard deviation were calculated using mathematical functions standard in most spreadsheet packages.

Table 2

XYZ Mutual
Historical Net Loss Ratios (LR)

Accident Year	Ultimate LR
1989	75.0%
1990	73.0%
1991	70.0%
1992	78.0%
1993	80.0%
1994	75.0%
1995	68.0%
1996	75.0%
1997	81.0%
Mean:	75.0%
SD:	4.3%

Distribution Comparison

	Standard Deviation (SD)			
Probability	1.0%	4.3%	10.0%	15.0%
0.01	72.7%	65.0%	51.7%	40.1%
0.05	73.4%	67.9%	58.6%	50.3%
0.15	74.0%	70.5%	64.6%	59.5%
0.25	74.3%	72.1%	68.3%	64.9%
0.35	74.6%	73.3%	71.1%	69.2%
0.50	75.0%	75.0%	75.0%	75.0%
0.65	75.4%	76.7%	78.9%	80.8%
0.75	75.7%	77.9%	81.7%	85.1%
0.95	76.6%	82.1%	91.4%	99.7%
0.99	77.3%	85.0%	98.3%	109.9%

XYZ Mutual's explicitly calculated standard deviation is 4.3%. For comparison purposes, four possible normal distributions have been provided using a mean loss ratio of 75.0% and standard deviations of 1.0%, 4.3%, 10.0% and 15.0% (see Appendix D for graphical display). For a standard deviation of 4.3%, the stochastically simulated loss ratios will be less than or equal to 77.9% three quarters of the time. Alternatively, the DFA model could use a skewed distribution depending on the line of business.

Lines with the possibility of catastrophes can be modeled using a split point ELR. An analysis can be performed using catastrophe modeling to estimate the probability of a catastrophe occurring (i.e. 1 in every 100 years). Based upon industry analysis, catastrophe modeling, and historical company catastrophe experience, the appropriate catastrophe ELR can be loaded into the DFA model along with the non-catastrophe ELR. The DFA model then stochastically simulates the line of business ELR by accident year based upon the catastrophe occurrence probability.

The ELR approach has a number of benefits over the FS approach:

- The ELR approach is much easier to understand and explain to insurance regulators and policyholders. As stated above, it is based directly on company provided data.
- The FS method requires the estimation of exposures which is sometimes difficult to obtain (e.g. General Liability, may use sales, square footage, or payroll) and the estimation of severity based upon a lognormal distribution or some other distribution which may not seem intuitive to the non-insurance reviewer.
- The ELR approach is easier to parameterize since estimates of the ELR and standard deviation are simple to derive. The FS approach requires more actuarial rigor.
- The ELR approach doesn't require the loading of reinsurance information on a contract by contract basis.

Accident year ultimate losses and ALAE are developed into calendar year using the payout pattern for each line of business. Payout patterns can be determined using internal company reports along with the external sources discussed previously. Unallocated loss adjustment expense (ULAE) can be calculated separately or loaded into the expected loss and ALAE ratio.

Invested Assets

The before-tax portfolio yield of the invested assets can be determined directly from the annual statement. The allocation of the invested assets to individual asset classes is important for tax considerations and requires a minimum of three asset classes: taxable investments, tax-exempt bonds and dividend-generating assets. Tax-exempt bonds and dividend-generating assets are used in the calculation of income taxes due to the removal of tax-exempt income, the dividends received deduction (DRD), and the subsequent tax proration of both items.

The model can be expanded to cover any number of different asset classes depending upon the investment strategy of the mutual company under review. The approach used by the authors combines expected returns, variation and correlation. For any given asset class, these three items must be defined in order to generate the outcome of events.

An important consideration for any appraisal range of value is the direction of future interest rates. Rising interest rates for a company that holds a majority of its invested assets in longer term bonds can be rather devastating if assets need to be sold in order to satisfy policyholder demands or the payment of dividends. Under the current interest rate environment where thirty year government bonds are hovering at yields of roughly 5%, a significant potential future risk lies in an upside swing in interest rates. The authors' DFA model can be run assuming a steady interest rate environment for the future simulation years, a falling then rising interest rate environment, or rising then falling interest rate environment. Our discussions with company management and insurance regulators point out that assuming a steady interest rate environment under the current interest rate conditions may result in a slight overstatement of the appraisal range of value depending upon how well the company has matched their assets and liabilities. Rising interest rates and the selling of bonds that are not held to maturity can result in capital losses, since the market value of bonds at the time of sale decrease from the amortized cost values shown on the annual statement. A company with an asset duration exceeding its liability duration by a large margin may require an explicit calculation of the possible capital losses under a rising interest rate scenario.

Non-Invested Assets

The DFA model can be programmed to handle non-invested assets in a number of different ways depending upon the size of the various non-invested assets. Agents' balances or uncollected premiums usually represent the largest non-invested asset on most balance sheets[2]. Agents balances flow through to the cash flow statement based upon the percentage of written premiums collected each year. The use of alternative assumptions to run-off the other assets usually has a minimal impact on the results of the demutualization analysis due to the small percentage of assets that are classified as non-invested assets when compared to the total balance sheet assets. A more detailed approach would be to develop collection/recovery patterns for other categories such as reinsurance recoverable on loss and LAE payments and federal income tax recoverable. For some of the smaller categories such as electronic data processing equipment and interest, dividends and real estate income due and accrued, the value added by individual estimation would be minimal.

Other Liabilities (excluding benefit accruals)

Similar to non-invested assets, the DFA model can be programmed to handle other liabilities in a number of different ways. Other liabilities exclude losses, LAE and unearned premium reserves, the three largest liability categories, and represent a small percentage of the total balance sheet liabilities. Other liabilities can be lumped together and treated like a single unpaid expense, similar to the treatment discussed above for non-invested assets and agents' balances. The assumptions used to run off the other liabilities usually has a minimal impact on the results of the demutualization analysis due to the small percentage of liabilities classified as other liabities. The excess of statutory reserves over statement reserves can be explicitly calculated and reflected as appropriate in the balance sheet liability and the surplus account.

Benefit Accruals

A simplifying assumption is to freeze the deferred compensation and post-retirement health benefit accruals at the December 31st value for the last historical year. A separate analysis of the materiality of the accrual may be required if there is a perception that the held accrual may be inadequate.

Other Income

Other income items such as finance and service charges not included in premiums and servicing carrier revenue can result in an increase in net income. It is important not to forget such cash flow items in the demutualization analysis. The authors recommend two ways of handling other income items; the first approach would allow for an explicit calculation of other income items as a percentage of net written premiums, the second approach would reduce the line of business expense ratios for any additional other income items.

Taxes

The provision for Federal Income Tax utilized in the DFA model reflects only taxes attributable to operations without any consideration of the effect of a sale of the business. Current federal corporate tax rates have been assumed throughout the ten year simulation period. The DFA model considers regular tax versus alternative minimum tax, including loss reserve discounting, revenue offset, tax-exempt income adjustments and the DRD, including proration. For the purpose of discounting loss reserves for federal tax, IRS discount factors or company payout patterns can be used in the model.

DFA Model Sample Analysis

Presented below is simplified illustration of an actual actuarial appraisal of economic value performed by the authors.

XYZ Casualty Mutual writes personal automobile insurance for the automobile liability (AL) and physical damage (PD) lines of business. XYZ currently has $4.3 million dollars of surplus as of December 31, 1998 and invests primarily in taxable bonds. A review of the historical loss and LAE ratios for XYZ indicated an expected loss ratio of 78.0% for AL and an expected loss and LAE ratio of 70% for PD. The standard deviation for both lines of business were selected at 5.0% based upon a review of XYZ's internal company reports and the Statement of Actuarial Opinion. Accident year ultimate loss and LAE ratios were simulated assuming a normal distribution and developed into calendar year cash flows using the below cumulative payout patterns by line of business:

	Age in Months							
	12	24	36	48	60	72	84	96
AL	0.400	0.700	0.850	0.900	0.970	0.980	0.990	0.995
PD	0.850	0.950	0.990	1.000	1.000	1.000	1.000	1.000

A number of simplifying assumptions were made to the DFA model for purpose of this example. AL and PD expenses where set equal to 28.0% in the model to reflect commissions, taxes, licensees, and fees, other acquisition expense and general expenses. Other income items such as finance and service charges from installment plans were assumed to be negligible. A majority of XYZ's taxable investments were placed in bonds, resulting in a yield on average assets over the simulation period of roughly 8% before taxes. Investments originally allocated to tax-exempt bonds and dividend generating assets by XYZ were reallocated to taxable bonds in order to avoid adjustments to tax-exempt income and the DRD.

A RRR or 87.5% was selected based upon XYZ's historical lapse ratio of 12.5%. A net liability to surplus ratio (NLSR) of 2:1 was selected to control the dividends (or capital contributions) made to the policyholder based upon a review of companies writing similar lines of business. Although a slightly lower ratio of 1.5:1 was indicated by the review of the other companies, the authors judgmentally selected a higher 2:1 ratio. Industry NLSR ratios have been lower in recent years due to the above average stock market returns over the last few years, resulting in an "overstated" surplus in the denominator. The selected 2:1 ratio, more reflective of longer term trends, maintains a balance between the insurance liabilities and the capital supporting them without unduly restricting the release of investor capital in the form of policyholder dividends.

Appendix E.2 and E.3 display XYZ's simplified balance sheet, income statement, cash flow statement, operating and leverage ratios, and the OCC analysis used to derive the actuarial appraisal value factors. It is important to note that the results displayed in these two appendices represent one simulation with no variability in the loss ratios, investment returns or written premiums. Appendix E.3 shows the net surplus flows to the policyholders based upon maintaining the selected 2:1 NLSR. The 1999 simulation year actually required a capital contribution of $100,971 by the policyholders in order to raise surplus to $5,071,240, resulting in the 2:1 ratio when compared to the loss & LAE reserves of $10,142,480. Simulation years 2000 and subsequent provide the payment of dividends to the policyholders.

The cumulative internal rate of return (IRR) of 15.3% is shown on Appendix E.3 under the title Operating Ratios. The IRR was derived using the December 31, 1998 surplus of $4,298,679 as the policyholders' initial investment, the net surplus flows derived from the model, and a return of the remaining surplus (i.e. remaining initial investment) at December 31, 2008 of $1,881,094. The 15.3% IRR can be used as a benchmark for analyzing the OCC desired by investors in XYZ Mutual. If the IRR is greater than the OCC, the appraisal value factor will exceed one. If the IRR is less than the OCC, the appraisal value factor will fall below one. Reviewing the OCC analysis shown on Appendix E.3, the resulting appraisal value factors (ratios to surplus) for the 10.0% (1.301), 12.5% (1.146) and 15.0% (1.016) OCC are all greater than 1.000, reflecting the fact that the IRR is greater than all three OCC's. The appraisal value factors (ratios to surplus) were derived using the ratio of the estimated company value simulated by the model to the company's actual December 31, 1998 surplus. The estimated company value for current policyholders was determined by taking the present value of estimated future policyholder dividends (or capital contributions), plus the remaining surplus at the end of ten years, discounted at the appropriate OCC.

Appendix E.4 displays a scatter graph of the results from running the DFA model one thousand times with the stochastic switch turned on. With a 12.5% OCC, the appraisal value factors range from a low of 0.72 to a high of 1.56, with an average appraisal value factor of 1.15 for the one thousand simulations. Appendix E.5 displays a frequency graph of the one thousand simulations, along with the eighty percent middle confidence interval. The appraisal factors based upon the eighty percent confidence interval range from a low of 1.00 to a high of 1.34, with an average appraisal value factor of 1.17.

The results shown in Appendix E.1 document the actuarial appraisal range of value for three different OCC's: 10.0%, 12.5% and 15.0%. Using an OCC of 12.5%, the company has an economic value between $4.3 million dollars and $5.8 million dollars. The low end of the range offers the policyholders the actual stated surplus as of December 31, 1997. The high end of the range offers the policyholders $1.5 million dollars more than the actual stated surplus as of December 31, 1998. As one would expect, selecting the 15.0% OCC results in a lowering of the economic value of the company and selecting the 10.0% OCC results in a raising of the economic value of the company.

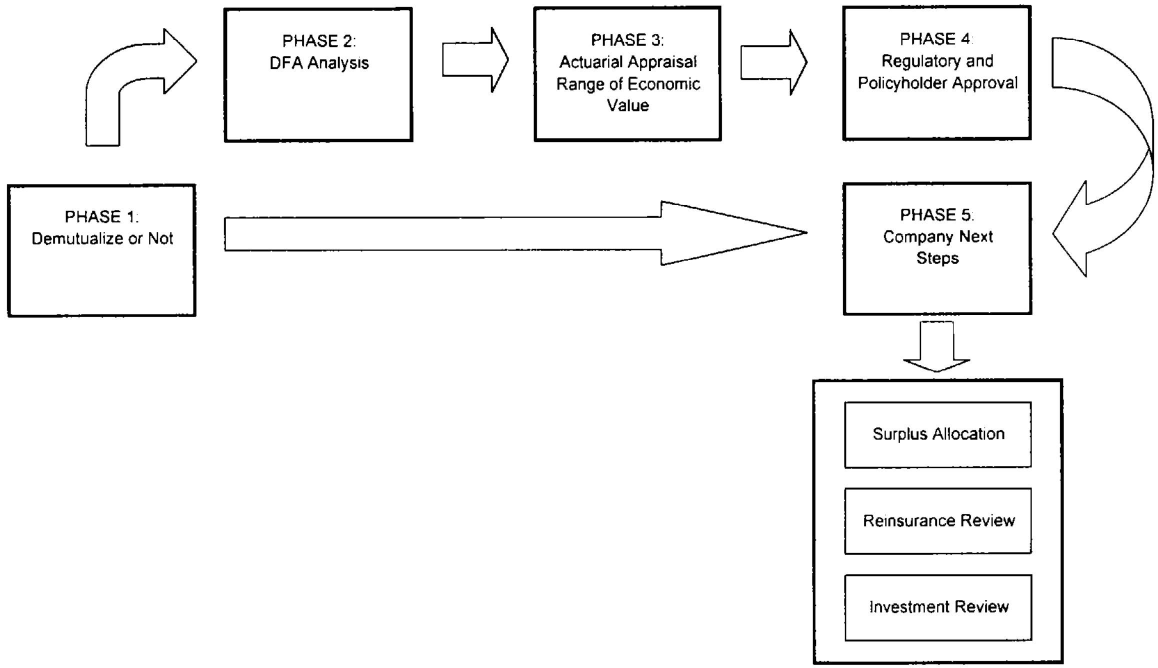
References

[1] A.M. Best Company, Inc., *Best's Aggregates & Averages*, United States Property-Casualty, 1997 Edition.

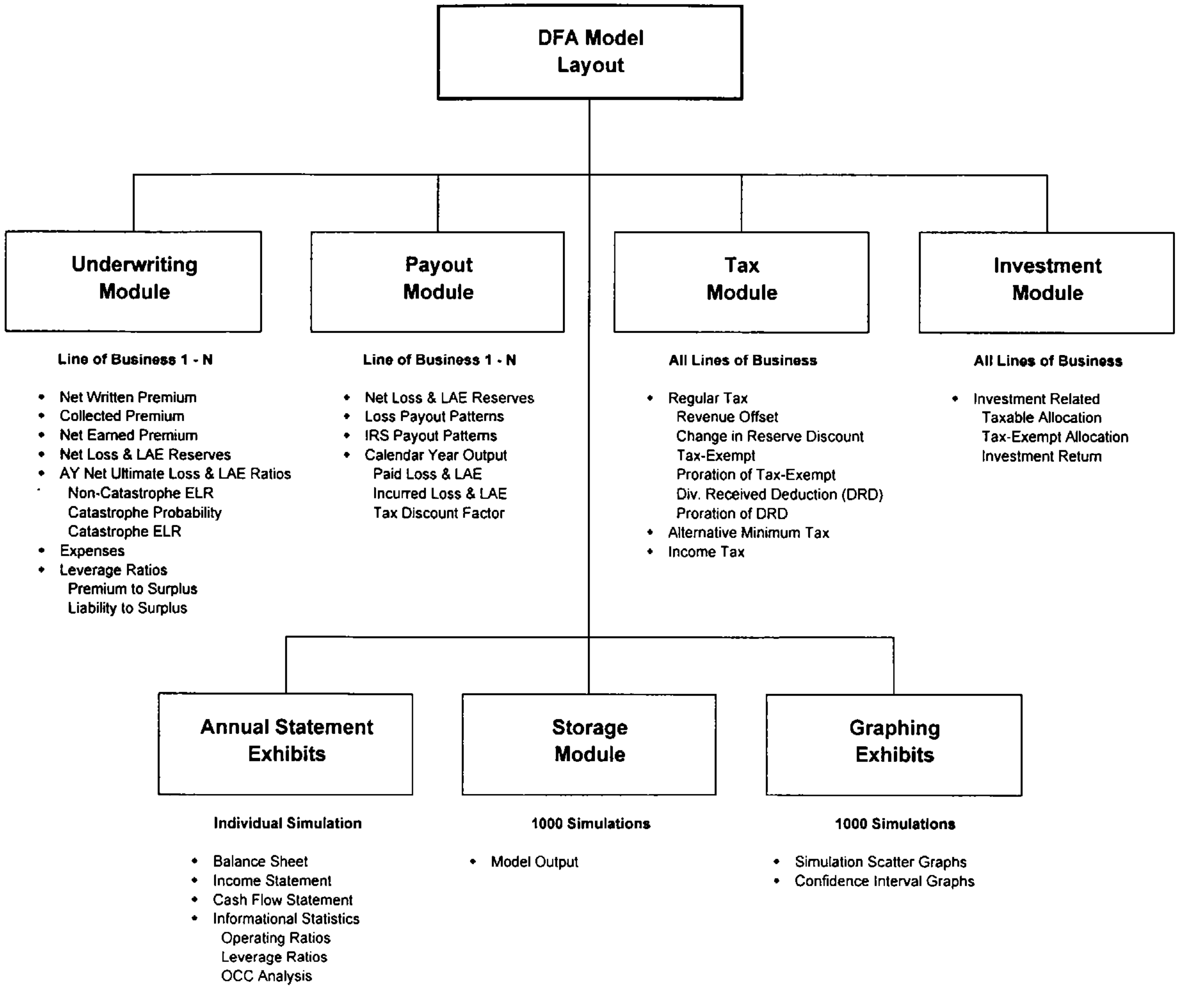
[2] Insurance Accounting and Systems Associations, *Property-Casualty Insurance Accounting* (Sixth Edition), 1994

APPENDIX A

DEMUTUALIZATION PROCESS



APPENDIX B


DFA Model Layout
Underwriting Module
Line of Business 1 - N
• Net Written Premium
• Collected Premium
• Net Earned Premium
• Net Loss & LAE Reserves
• AY Net Ultimate Loss & LAE Ratios
Non-Catastrophe ELR
Catastrophe Probability
Catastrophe ELR
• Expenses
• Leverage Ratios
Premium to Surplus
Liability to Surplus
Payout Module
Line of Business 1 - N
• Net Loss & LAE Reserves
• Loss Payout Patterns
• IRS Payout Patterns
• Calendar Year Output
Paid Loss & LAE
Incurred Loss & LAE
Tax Discount Factor
Tax Module
All Lines of Business
• Regular Tax
Revenue Offset
Change in Reserve Discount
Tax-Exempt
Proration of Tax-Exempt
Div. Received Deduction (DRD)
Proration of DRD
• Alternative Minimum Tax
• Income Tax
Investment Module
All Lines of Business
• Investment Related
Taxable Allocation
Tax-Exempt Allocation
Investment Return
Annual Statement Exhibits
Individual Simulation
• Balance Sheet
• Income Statement
• Cash Flow Statement
• Informational Statistics
Operating Ratios
Leverage Ratios
OCC Analysis
Storage Module
1000 Simulations
• Model Output
Graphing Exhibits
1000 Simulations
• Simulation Scatter Graphs
• Confidence Interval Graphs

XYZ CASUALTY COMPANY MUTUAL
100.0% COMBINED RATIO

	1/1/98	12/31/98	12/31/99	12/31/00	12/31/01	12/31/02
		ANNUAL STATEMENT				
BALANCE SHEET						
ASSETS						
BONDS	747	792	840	890	943	1,000
LIABITIES						
LOSS RESERVE	0	0	0	0	0	0
SURPLUS	747	792	840	890	943	1,000
INCOME STATEMENT						
PREMIUMS EARNED		747	792	840	890	943
LOSSES INCURRED		523	554	588	623	660
OTHER UNDERWRITING EXPENSE		224	238	252	267	283
NET UNDERWRITING GAIN OR (LOSS)		0	0	0	0	0
NET INVESTMENT GAIN OR (LOSS)		45	48	50	53	57
NET INCOME		45	48	50	53	57
SURPLUS PRIOR YEAR		747	792	840	890	943
NET INCOME		45	48	50	53	57
SURPLUS YEAR END		792	840	890	943	1,000
COMBINED RATIO		100.0%	100.0%	100.0%	100.0%	100.0%
ANNUAL RETURN		6.0%	6.0%	6.0%	6.0%	6.0%

12/31/02 SURPLUS:	1,000
12/31/02 SURPLUS DISCOUNTED @OCC:	621
BEGINNING SURPLUS (INITIAL INVESTMENT):	747
RATIO OF DISCOUNTED SURPLUS TO INITIAL SURPLUS:	0.831

NOTE:

ASSUMES PREMIUM AND LOSSES OCCUR ON 12/31/XX
ASSUMES A 1:1 PREMIUM TO SURPLUS RATIO AT THE BEGINNING OF THE YEAR
ASSUMES AN EXPECTED LOSS RATIO OF 70.0%
ASSUMES AN OTHER UNDERWRITING EXPENSE RATIO OF 30.0%
ASSUMES AN ANNUAL BOND RETURN OF 6.0%
ASSUMES NO TAXES OR INVESTMENT RELATED EXPENSES
ASSUMES SURPLUS RETURNED AT END OF YEAR 5
ASSUMES OPPORTUNITY COST OF CAPITAL (OCC) OF 10.0%

XYZ CASUALTY COMPANY MUTUAL
90.0% COMBINED RATIO

	1/1/98	12/31/98	12/31/99	12/31/00	12/31/01	12/31/02
		ANNUAL STATEMENT				
BALANCE SHEET						
ASSETS						
BONDS	747	867	1,006	1,166	1,353	1,569
LIABITIES						
LOSS RESERVE	0	0	0	0	0	0
SURPLUS	747	867	1,006	1,166	1,353	1,569
INCOME STATEMENT						
PREMIUMS EARNED		747	867	1,006	1,166	1,353
LOSSES INCURRED		448	520	603	700	812
OTHER UNDERWRITING EXPENSE		224	260	302	350	406
NET UNDERWRITING GAIN OR (LOSS)		75	87	101	117	135
NET INVESTMENT GAIN OR (LOSS)		45	52	60	70	81
NET INCOME		120	139	161	187	216
SURPLUS PRIOR YEAR		747	867	1,006	1,166	1,353
NET INCOME		120	139	161	187	216
SURPLUS YEAR END		867	1,006	1,166	1,353	1,569
COMBINED RATIO		90.0%	90.0%	90.0%	90.0%	90.0%
ANNUAL RETURN		16.0%	16.0%	16.0%	16.0%	16.0%

12/31/02 SURPLUS:	1,569
12/31/02 SURPLUS DISCOUNTED @OCC:	975
BEGINNING SURPLUS (INITIAL INVESTMENT):	747
RATIO OF DISCOUNTED SURPLUS TO INITIAL SURPLUS:	1.304

NOTE:

ASSUMES PREMIUM AND LOSSES OCCUR ON 12/31/XX
ASSUMES A 1:1 PREMIUM TO SURPLUS RATIO AT THE BEGINNING OF THE YEAR
ASSUMES AN EXPECTED LOSS RATIO OF 60.0%
ASSUMES AN OTHER UNDERWRITING EXPENSE RATIO OF 30.0%
ASSUMES AN ANNUAL BOND RETURN OF 6.0%
ASSUMES NO TAXES OR INVESTMENT RELATED EXPENSES
ASSUMES SURPLUS RETURNED AT END OF YEAR 5
ASSUMES OPPORTUNITY COST OF CAPITAL (OCC) OF 10.0%

XYZ CASUALTY COMPANY MUTUAL
105.0% COMBINED RATIO

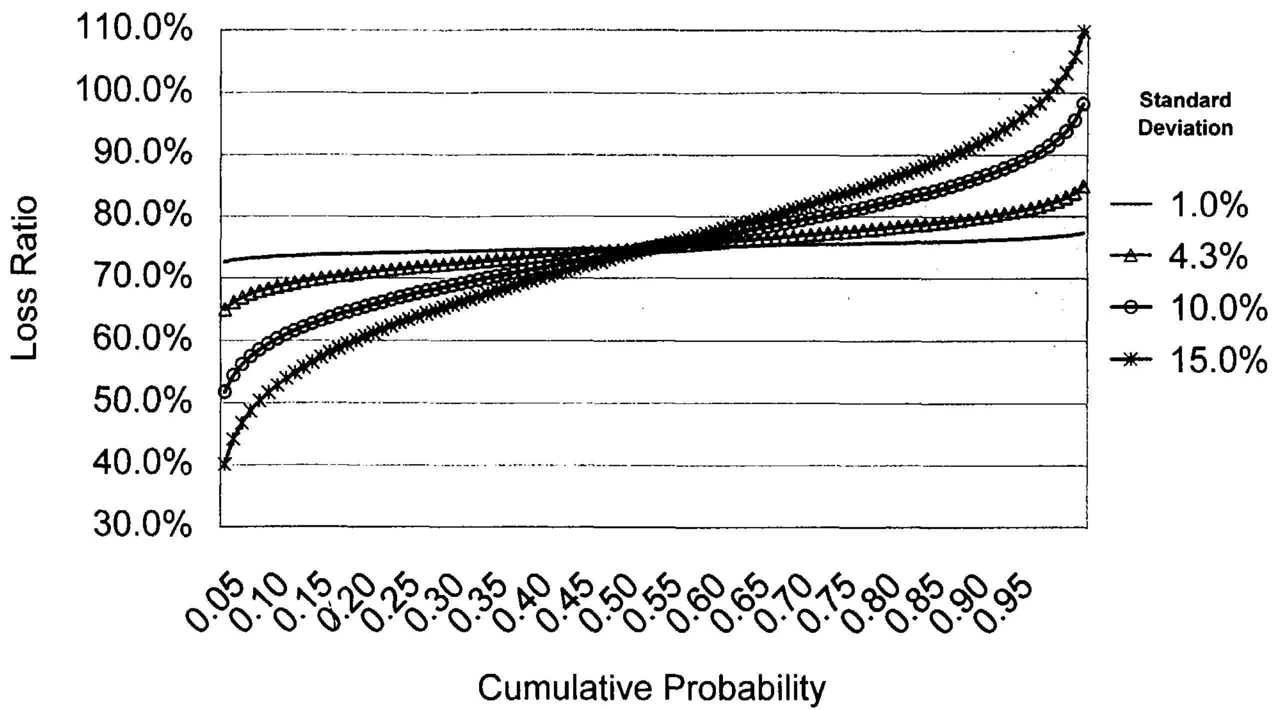
	1/1/98	12/31/98	12/31/99	12/31/00	12/31/01	12/31/02
		ANNUAL STATEMENT				
BALANCE SHEET						
ASSETS						
BONDS	747	755	762	770	778	785
LIABILITIES						
LOSS RESERVE	0	0	0	0	0	0
SURPLUS	747	755	762	770	778	785
INCOME STATEMENT						
PREMIUMS EARNED		747	755	762	770	778
LOSSES INCURRED		560	566	572	577	583
OTHER UNDERWRITING EXPENSE		224	226	229	231	233
NET UNDERWRITING GAIN OR (LOSS)		-37	-38	-38	-38	-39
NET INVESTMENT GAIN OR (LOSS)		45	45	46	46	47
NET INCOME		7	8	8	8	8
SURPLUS PRIOR YEAR		747	755	762	770	778
NET INCOME		7	8	8	8	8
SURPLUS YEAR END		755	762	770	778	785
COMBINED RATIO		105.0%	105.0%	105.0%	105.0%	105.0%
ANNUAL RETURN		1.0%	1.0%	1.0%	1.0%	1.0%

12/31/02 SURPLUS:	785
12/31/02 SURPLUS DISCOUNTED @OCC:	488
BEGINNING SURPLUS (INITIAL INVESTMENT):	747
RATIO OF DISCOUNTED SURPLUS TO INITIAL SURPLUS:	0.653

NOTE:

ASSUMES PREMIUM AND LOSSES OCCUR ON 12/31/XX
ASSUMES A 1:1 PREMIUM TO SURPLUS RATIO AT THE BEGINNING OF THE YEAR
ASSUMES AN EXPECTED LOSS RATIO OF 75.0%
ASSUMES AN OTHER UNDERWRITING EXPENSE RATIO OF 30.0%
ASSUMES AN ANNUAL BOND RETURN OF 6.0%
ASSUMES NO TAXES OR INVESTMENT RELATED EXPENSES
ASSUMES SURPLUS RETURNED AT END OF YEAR 5
ASSUMES OPPORTUNITY COST OF CAPITAL (OCC) OF 10.0%

XYZ MUTUAL LOSS RATIO DISTRIBUTION



XYZ CASUALTY MUTUAL COMPANY
Actuarial Appraisal of Economic Value

	12/31/98	10% OCC			12.5% OCC			15% OCC		
	Surplus	Low	Midpoint	High	Low	Midpoint	High	Low	Midpoint	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Appraisal Value Factor		1.14	1.32	1.50	1.00	1.17	1.34	0.88	1.04	1.20
Estimated Surplus (11)	4,299	4,900	5,674	6,448	4,299	5,029	5,760	3,783	4,471	5,158
Value Added (12)		602	1,376	2,149	0	731	1,462	(516)	172	860

(1) XYZ Casualty Company Mutual December 31, 1998 Surplus
(2)-(4) Refer to Appendix E.6, Middle 80% Confidence Interval Range
(5)-(7) Refer to Appendix E.5, Middle 80% Confidence Interval Range
(8)-(10) Refer to Appendix E.7, Middle 80% Confidence Interval Range
(11) Estimated Surplus = Appraisal Value Factor x (1)
(12) = (11) - (1)

XYZ CASUALTY MUTUAL COMPANY
ANNUAL STATEMENT

	Historical					Simulation Years					
	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Balance Sheet											
Assets											
Invested Assets	17,219,126	18,443,775	17,515,258	15,975,479	14,356,988	12,735,926	11,227,273	9,860,678	8,639,243	7,559,339	6,614,422
Total Assets	17,219,126	18,443,775	17,515,258	15,975,479	14,356,988	12,735,926	11,227,273	9,860,678	8,639,243	7,559,339	6,614,422
Liabilities											
Loss & Loss Adjustement Expense Reserves	9,228,962	10,142,483	9,792,643	9,001,648	8,128,738	7,228,354	6,380,368	5,607,364	4,913,877	4,299,644	3,762,189
Unearned Premium Reserve	3,691,485	3,230,049	2,826,293	2,473,007	2,163,881	1,893,396	1,656,721	1,449,631	1,268,427	1,109,874	971,140
Total Liabilities	12,920,447	13,372,533	12,618,937	11,474,655	10,292,619	9,121,749	8,037,089	7,056,995	6,182,304	5,409,518	4,733,328
Surplus	4,298,679	5,071,242	4,896,322	4,500,824	4,064,369	3,614,177	3,190,184	2,803,682	2,456,939	2,149,822	1,881,094
Surplus + Liabilities	17,219,126	18,443,775	17,515,258	15,975,479	14,356,988	12,735,926	11,227,273	9,860,678	8,639,243	7,559,339	6,614,422
Income Statement											
Underwriting											
Net Earned Premium	18,583,667	17,362,950	15,192,581	13,293,508	11,631,820	10,177,842	8,905,612	7,792,411	6,818,359	5,966,064	5,220,306
Loss and Loss Expenses Incurred	14,095,264	12,984,023	11,361,011	9,940,891	8,698,284	7,610,986	6,659,621	5,827,173	5,098,761	4,461,436	3,903,741
Underwriting Expenses Incurred	5,368,419	4,732,424	4,140,871	3,623,262	3,170,354	2,774,060	2,427,303	2,123,890	1,858,403	1,626,103	1,422,840
Net Underwriting Gain or (Loss)	(880,016)	(353,498)	(309,301)	(270,645)	(236,819)	(207,204)	(181,312)	(158,652)	(138,805)	(121,475)	(106,275)
Investment & Other Income											
Net Investment Income Earned	1,200,000	1,381,474	1,432,986	1,344,624	1,221,284	1,093,436	968,235	852,632	748,314	655,369	573,449
Net Income Before Tax	319,984	1,027,976	1,123,685	1,073,979	984,465	886,232	786,924	693,980	609,509	533,894	467,174
Federal Income Tax	50,000	356,387	355,587	326,139	296,287	263,553	232,302	203,905	178,389	155,924	136,439
Net Income After Tax	269,984	671,589	768,098	747,840	688,178	622,679	554,622	490,075	431,121	377,971	330,735
Capital and Surplus Account											
Surplus, December 31 Prior Year	4,028,695	4,298,679	5,071,242	4,896,322	4,500,824	4,064,369	3,614,177	3,190,184	2,803,682	2,456,939	2,149,822
Gains or (Losses) In Surplus											
Net Income After Tax	269,984	671,589	768,098	747,840	688,178	622,679	554,622	490,075	431,121	377,971	330,735
+ Capital Contribution / - Dividend to PH		100,974	(943,018)	(1,143,337)	(1,124,633)	(1,072,871)	(978,615)	(876,576)	(777,864)	(685,087)	(599,462)
Surplus, December 31 Current Year	4,298,679	5,071,242	4,896,322	4,500,824	4,064,369	3,614,177	3,190,184	2,803,682	2,456,939	2,149,822	1,881,094

NOTE: Results are based on expected values, before simulating variability

XYZ CASUALTY MUTUAL COMPANY
ANNUAL STATEMENT

	Historical					Simulation Years					
	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Cash Flow											
Collected Premium		16.901.514	14 788 825	12 940.222	11.322 694	9.907 357	8.668.938	7 585.320	6.637 155	5.807 511	5 081 572
Net Loss and LAE Paid		12 070 502	11 710.851	10 731.886	9.571.195	8.511.370	7.507.607	6 600.176	5.792 248	5 075.670	4.441.196
Underwriting Expense Paid		4 732 424	4 140.871	3.623.262	3.170 354	2.774.060	2.427.303	2.123.890	1.858.403	1.626.103	1.422 840
Net Cash From Underwriting		98.588	(1.062.897)	(1.414 926)	(1.418 855)	(1.378.073)	(1.265.972)	(1.138.745)	(1.013 496)	(894 262)	(782 464)
Investment Income Recieved		1 381.474	1.432.986	1.344.624	1.221.284	1.093.436	968.235	852.632	748 314	655.369	573.449
Taxes Paid		356.387	355 587	326.139	296.287	263.553	232.302	203.905	178 389	155.924	136.439
Net Cash From Operations		1 123.675	14.502	(396.442)	(493 858)	(548 190)	(530.039)	(490.019)	(443 571)	(394.816)	(345.455)
Net Surplus Flows		100.974	(943 018)	(1.143.337)	(1.124.633)	(1 072.871)	(978.615)	(876.576)	(777 864)	(685.087)	(599.462)
Total Cash Flow		1 224 649	(928 516)	(1 539.779)	(1 618 492)	(1 621.061)	(1.508.654)	(1.366 595)	(1 221 435)	(1 079.904)	(944.917)
Operating Ratios											
Loss and Loss Expense Ratio (EP)	75 8%	74 8%	74 8%	74 8%	74 8%	74 8%	74 8%	74.8%	74 8%	74 8%	74 8%
PP Auto Liab		78 0%	78 0%	78 0%	78 0%	78 0%	78 0%	78 0%	78 0%	78 0%	78 0%
PP Auto Phys Dam		70 0%	70 0%	70 0%	70 0%	70 0%	70 0%	70 0%	70 0%	70 0%	70 0%
Underwriting Expense Ratio (WP)	27 8%	28 0%	28 0%	28 0%	28 0%	28 0%	28 0%	28 0%	28 0%	28 0%	28 0%
Combined Ratio	103 6%	102 8%	102 8%	102 8%	102 8%	102 8%	102 8%	102 8%	102 8%	102 8%	102 8%
Yield on Average Invested Assets	7 2%	7 7%	8 0%	8 0%	8 1%	8 1%	8 1%	8 1%	8 1%	8 1%	8 1%
Percent Non-Invested Assets	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
Surplus Flows For IRR	(4.298.679)	(100.974)	943 018	1.143.337	1.124 633	1.072.871	978.615	876.576	777.864	685.087	2 480.557
Cumulative IRR	15 3%										
Leverage Ratios											
Net Written Premium	19 316.016	16.901.514	14.788 825	12 940.222	11 322 694	9.907 357	8 668.938	7 585.320	6 637 155	5 807 511	5 081.572
Premium to Surplus	4 493	3 333	3 020	2 875	2 786	2 741	2 717	2 705	2 701	2 701	2 701
Net L&LAE to Surplus	2 147	2 000	2 000	2 000	2 000	2 000	2 000	2 000	2 000	2 000	2 000
Invested Assets to Surplus	4 006	3 637	3 577	3 549	3 532	3 524	3 519	3 517	3 516	3 516	3 516
Other Liabilities to Surplus	-	-	-	-	-	-	-	-	-	-	-
Opportunity Cost of Capital (OCC) Analysis											
+ Capital Contribution / - Dividend to PH		100.974	(943.018)	(1.143.337)	(1.124.633)	(1 072.871)	(978.615)	(876 576)	(777.864)	(685.087)	(599 462)
Low OCC - 10 0%		91 794	(779 354)	(859.006)	(768 140)	(666.169)	(552.403)	(449.822)	(362.879)	(290.544)	(231.119)
Midpoint OCC - 12 5%		89.754	(745 101)	(803.002)	(702.103)	(595.367)	(482.722)	(384.346)	(303.168)	(237.341)	(184.602)
High OCC - 15 0%		87.803	(713 057)	(751.763)	(643.013)	(533.407)	(423.082)	(329.537)	(254.285)	(194.745)	(148.178)

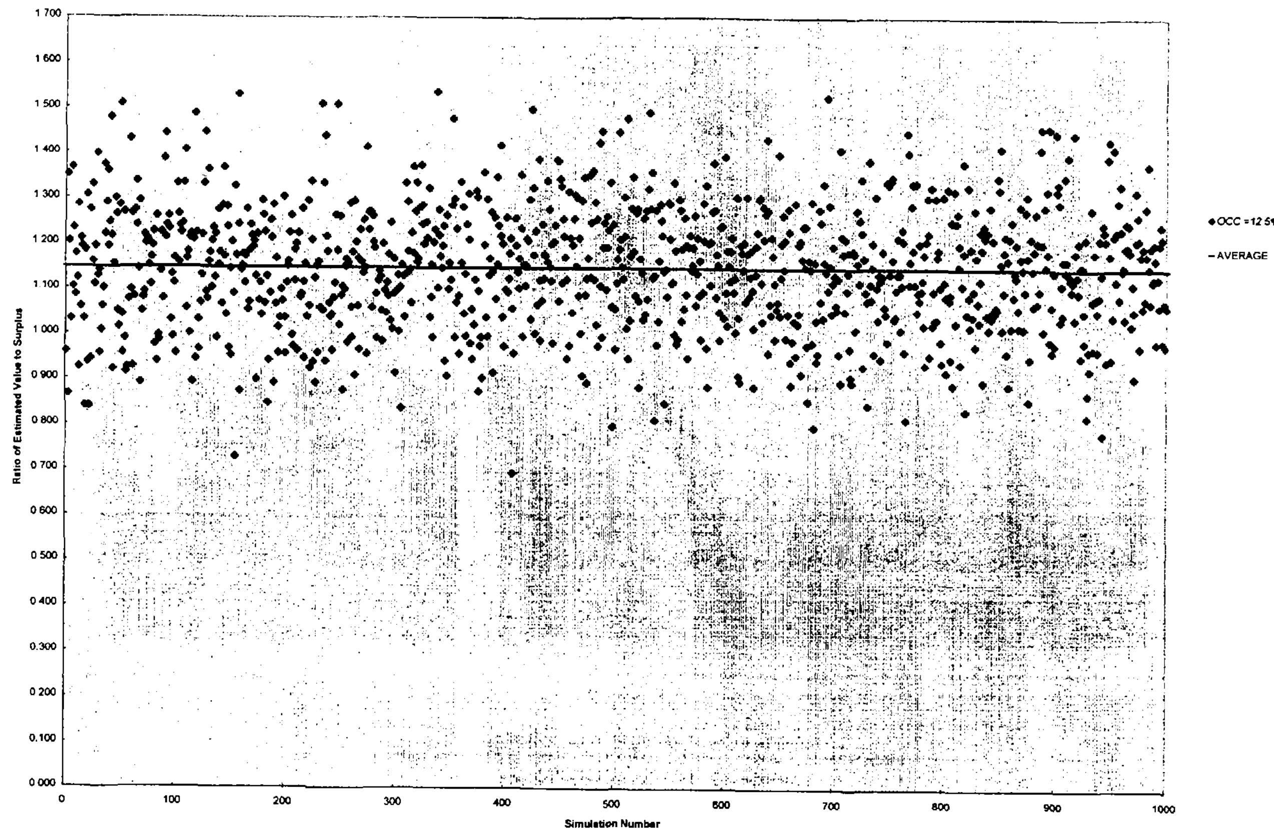
(1)	Statutory Surplus @12/31/98	4,298.679
(2)	Reserve Redundancy/(Inadequacy)	-
(3)	Market Value Adjustment (Schedule DM)	-
(4)	Surplus Adjustments	-
		10 Year
(5)	Estimated Value - 10 0%	5,592,884
(6)	Estimated Value - 12 5%	4 927,273
(7)	Estimated Value - 15 0%	4.368,241
(8)	Ratio to Surplus - 10 0%	1 301
(9)	Ratio to Surplus - 12 5%	1 146
(10)	Ratio to Surplus - 15 0%	1 016

Note
(1) 1998 Annual Statement
(2) 1998 Actuarial Report and Internal Analysis
(3) Schedule DM of the Annual Statement
(4) = (2) + (3)
(5) = (4) - CC/Div to PH + Return of Ending Surplus discounted at the low OCC
(6) = (4) - CC/Div to PH + Return of Ending Surplus discounted at the midpoint OCC
(7) = (4) - CC/Div to PH + Return of Ending Surplus discounted at the high OCC
(8) = (5) / (1)
(9) = (6) / (1)
(10) = (7) / (1)

NOTE Results are based on expected values, before simulating variability

XYZ CASUALTY MUTUAL COMPANY

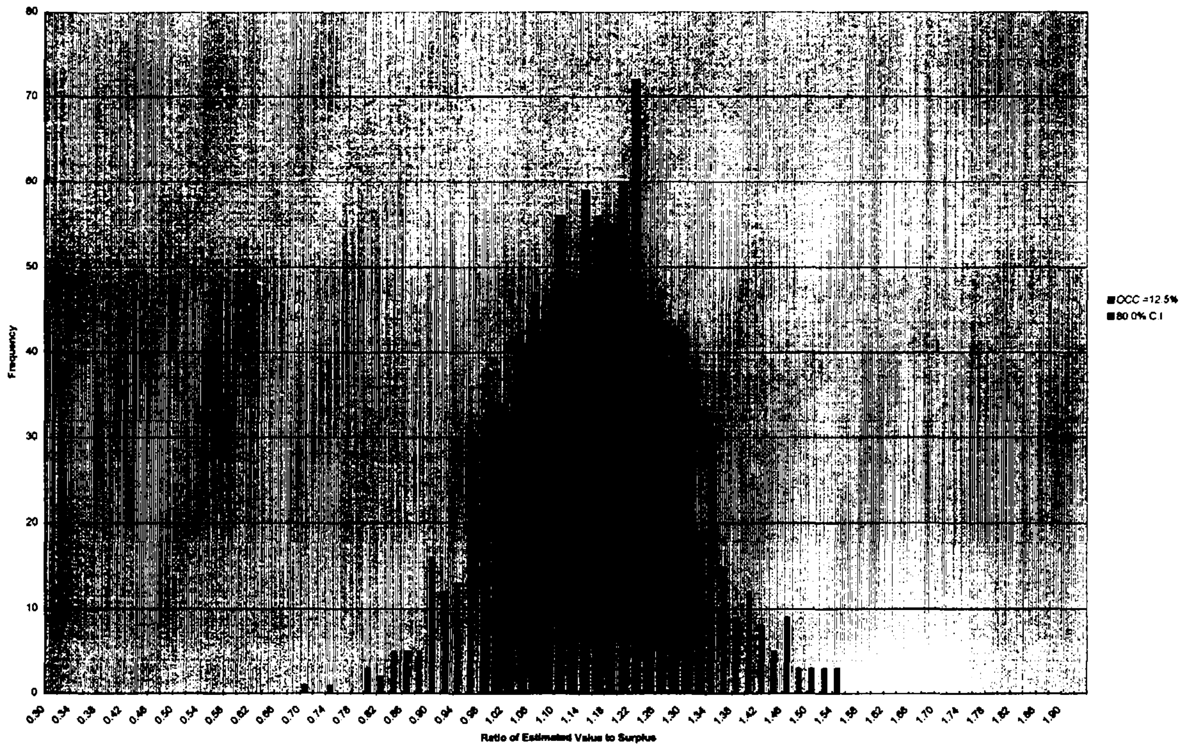
SIMULATION OF ESTIMATED COMPANY VALUE TO 12/31/98 STATUTORY SURPLUS
ASSUMING SURPLUS RETURNED AT END OF YEAR 2008



APPENDIX E.5

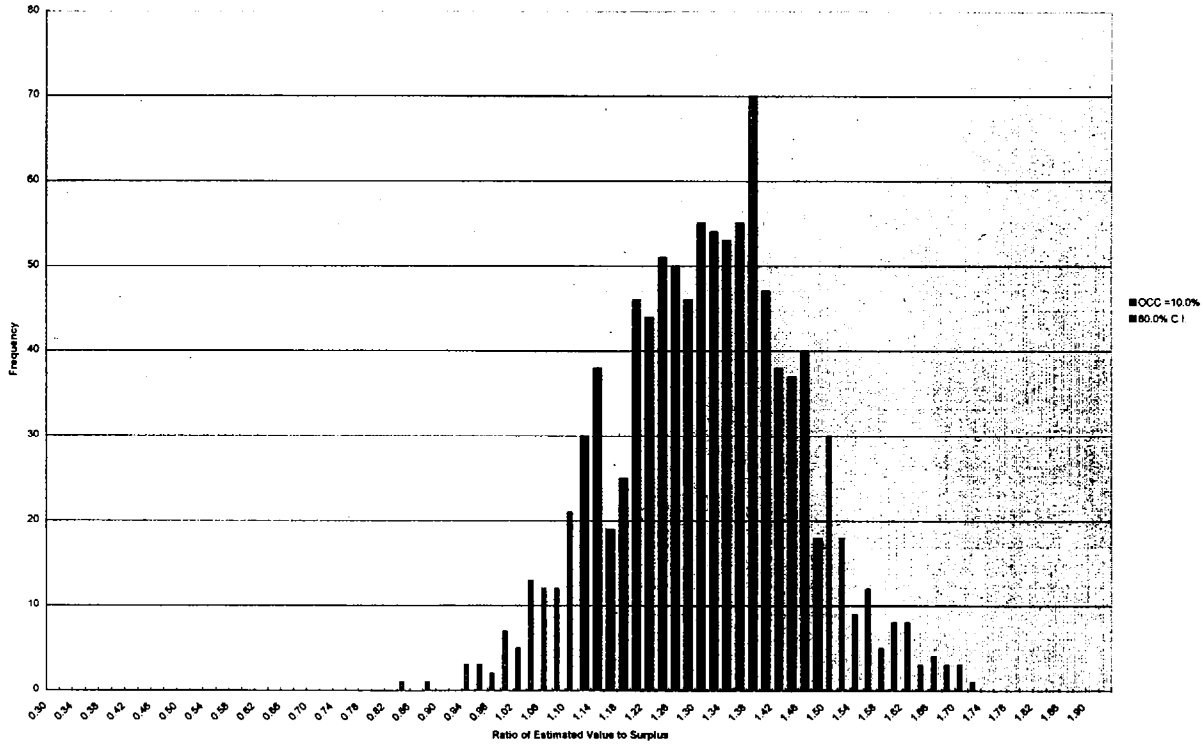
XYZ CASUALTY MUTUAL COMPANY

DISTRIBUTION OF ESTIMATED COMPANY VALUE TO 12/31/98 STATUTORY SURPLUS
ASSUMING SURPLUS RETURNED AT END OF YEAR 2008



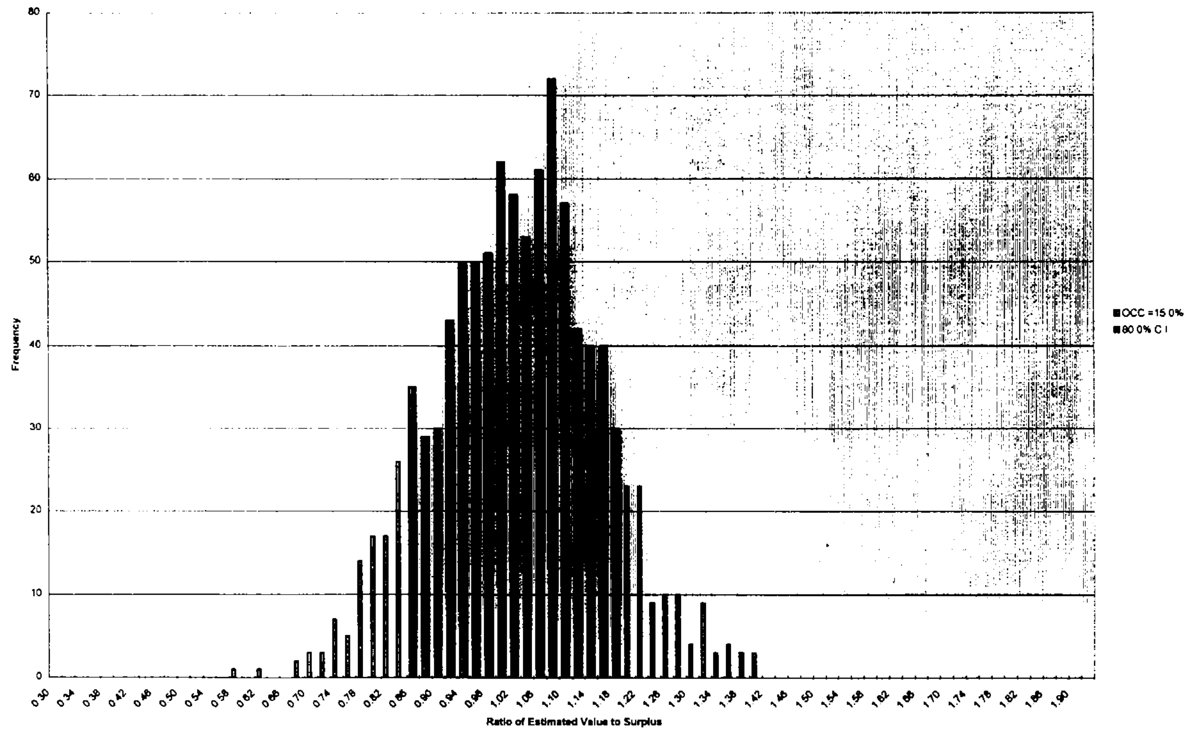
XYZ CASUALTY MUTUAL COMPANY

DISTRIBUTION OF ESTIMATED COMPANY VALUE TO 12/31/98 STATUTORY SURPLUS
ASSUMING SURPLUS RETURNED AT END OF YEAR 2008



XYZ CASUALTY MUTUAL COMPANY

DISTRIBUTION OF ESTIMATED COMPANY VALUE TO 12/31/98 STATUTORY SURPLUS
ASSUMING SURPLUS RETURNED AT END OF YEAR 2008



Y2K—A Regulatory Response

Jose Montemayor, Betty Patterson, and
Holmes Gwynn, FCAS, MAAA

Y2K – A Regulatory Response

Jose Montemayor, Betty Patterson, and Holmes Gwynn

February 1999

Abstract

Everyone has heard or read about the Year 2000 (Y2K) problem that refers to the potential for date-reliant electronic systems to fail because they were not designed to read four digits. In the insurance industry, the importance is particularly acute because the contracted product is delivered in the future, crossing date lines. Regulators across the country and throughout the world are confronted with monitoring the level of preparedness of their constituency for the Y2K. Like insurance companies, insurance regulators have a more difficult task because of the complexities and forms of insurance and reinsurance, as well as the industry's heavy reliance on business partners and vendors.

Insurance companies must have planned adequately and provided for their internal systems, such as claims processing and accounting, to be Y2K compliant. They also must have checked their external vendors, service providers and other business partners to be sure that those companies will be ready. For the property and casualty segment of the industry, regulators must ensure that insurers have assessed their potential liability for exposure under policies issued and addressed liquidity issues if their investment markets are temporarily halted.

Because there is no precedence, little reliable data is available on the cost of correcting the Y2K problem or the potential impact on the solvency of individual insurance companies or of the industry.

This paper will discuss the efforts by the Texas Department of Insurance (TDI) to assess the Y2K problem and to provide an appropriate regulatory response. The paper also reviews the material factors that bear on the Y2K issue and concludes with recommendations to the industry, as well as provide insights into the future direction of the response to the Y2K challenge.

Y2K – A Regulatory Response

Introduction

Clearly, the early designers of computer coding had no idea that their decision to use two digits instead of four to describe a year in a date would have such a material impact. These computer code pioneers made their decision for economic reasons when the price of a megabyte of memory was approximately one thousand more than today's cost. They likely assumed a much earlier replacement of the coding conventions and did not envision today's widespread use of computer applications in every facet of life.

Today an insurance company's decision to (1) re-code information systems with updated four-digit versions, (2) replace systems, or (3) do nothing may determine the survival of the company itself. The costs of assessment, remediation and testing are high. The result of doing nothing, or not enough, may mean policyholders are unable to get policy service, or worse, unable to collect on their policies at a time of need

Fundamentally, insurance regulators want to be sure that all insurers can accurately underwrite and issue policies, collect premiums, process and pay claims, as well as account and report for all of their functions, in a Y2K environment. Regulators must assess company systems, the business partners of insurers, and understand the Y2K impact resulting from litigation, legislation, property and liability exposure, and modification to reinsurance. For example, it will be necessary to take a fresh look at the semantics associated with the word "fortuitous" since it will play a major role in deciding whether losses are covered.

Texas statutes relating to examination and rehabilitation authority provide the basis for the Department of Insurance to assess the preparedness of the insurance industry operating in Texas. These statutes provide the authority to take action if company management fails to prepare for Y2K.

The Department's approach toward assessing the Y2K preparedness of the insurance industry began with a mandatory examination survey of approximately 3,400 insurers and insurance-related entities. The Department used resources from many disciplines, including information systems specialists, examiners, analysts, actuaries, attorneys, rate and form technicians and planners for both the survey design and the analysis of survey results. Because staff and financial resources are limited, the Department is using outside consultants to collect survey data, to evaluate plans, and to assist company management in correcting system problems.

Based on survey results and financial indicators, each company was confidentially scored. That provided a starting point to further assess their Y2K preparedness. Most companies demonstrated that their Y2K planning was sound and/or the lines of business they wrote were of minor concern, and, therefore, no further action was necessary.

However, responses from more than 1000 companies raised concerns and prompted additional attention.

While the survey was designed to determine Y2K systems compliance, it also was designed to gain an understanding of each company's underwriting exposure. The emphasis of this paper will be on that exposure, delving into the Y2K insurance risk within the commercial property and casualty industry.

As of this writing, a great deal continues to evolve. The background provided here will, hopefully, help those who have yet to be directly involved in Y2K preparation to better understand their role as the new year approaches.

Part 1 – Insurance Coverage Considerations

Insurance and coverage issues need to be evaluated their impact estimated. The questions include the determination of coverage based on policy language and the classes of business written with Y2K exposures that generate serious claims. The actuary will have a very useful role in the preliminary and ongoing Y2K analysis to estimate the frequency and severity of these potential claims.

Policy Triggers

Disputes already have arisen in the computer hardware and software industry over which policies provide coverage. Most insurers argue that the policy in force when the damage actually occurred should be responsible for payment. This has led some experts to suggest that the triggering for the Y2K coverage and occurrence will be the same trigger as used in asbestos and pollution coverage cases; the manifestation and exposure trigger. This issue will likely be determined early in the process and have a significant impact in determining what is and what is not insured and who is responsible.

Initial Commercial Property and Personal Injury Losses

The initial Y2K losses and claims will largely entail first-party property. Such claims may be extensive if an automated maintenance system fails and machinery shuts down. Part of the worldwide power grid could conceivably shut down, resulting in property loss to equipment such as high-temperature and high-pressure applications, life and safety systems, medical surveillance and monitoring equipment and security systems.

A second tier of claims will be for business interruption. While there will be claims for shutdowns, there also will be claims for business slowdowns, where the volume of work that normally runs through the insured system is diminished as a result of a Y2K problem.

Current industry thinking is that business interruption policies may provide little coverage for Y2K because such policies are written on a "named" peril basis. It is highly unlikely that Y2K will be added to the list of such perils. Even if primary insurers wanted to, their reinsurers may balk, regardless of premium. Even with an "all-risk" policy, most forms state that business interruption must arise out of direct physical loss to covered property and must be fortuitous. These defenses for claim denial are likely to be tested in court, producing another element of uncertainty as well as associated defense costs.

Examples of business interruption situations include those businesses that depend on vendors and suppliers that may be highly mechanized, such as banks that process checks, and retail stores that rely on credit card verification systems. The power industry is heavily dependent on computers with embedded systems and date sensitive programs that may result in an inability to provide customers with electricity and may result in significant loss of income.

Several major insurers have reviewed every Standard Industrial Code (SIC) for Y2K exposure, ranking them accordingly. Major classes ranked for property or business income loss potential include:

- Energy companies
- Security systems and companies
- Utilities
- Transportation (particularly aviation)
- Health care
- Financial services industries
- Governments

The oil and gas industry faces problems because of its dependency on highly sophisticated, computer-controlled data gathering for oil and gas exploration. Data can be corrupted, rendering faulty analysis, and emergency systems can cut down pipeline flow.

The airlines face service interruptions because of the embedded chips that can shut down equipment for automated maintenance checks.

Health care is also a concern because of embedded chips that depend on timing devices to keep functioning. The most commonly mentioned example is pacemakers.

The financial services industries that focus on managing assets and liabilities will face personal injury exposure because of invasions of privacy, security breakdowns and on-premise injuries at ATMs and branch locations.

The emergency response industry (police, fire and medical) faces the prospect that many alarms will go off at once, triggering an overflow of calls, preventing real emergencies from being timely addressed.

Once these losses have occurred, the question turns to who is liable. The process of affixing the responsibility will likely continue for years to come. Regulators, as well as company managements, will need the related loss data for years to come. Actuaries will be called upon to estimate and re-estimate ultimate loss and loss adjustment costs in much the same way environmental losses are estimated today.

General Liability Issues

The general liability questions center on coverage issues, including the definition of occurrence and product liability coverage. Management liability policies will center on errors and omissions (E&O) coverage and directors and officers (D&O) coverage.

General liability insurance provides third party coverage for property damage, bodily injury and personal injury not "expected or intended" by the insured. Property damage to the insured's own property or damage to products of the insured, is typically excluded if caused by a deficiency in the insured's work. For that reason, many Y2K claims may not involve that third party aspect. Those that do will have to stand up to the rigor of being unexpected or unintended. Further complications will arise as downstream causes and effects are considered in determining fault.

Another special concern may be ERISA claims. Fiduciaries have responsibility for payment of benefits and the administration of employment benefit plans. To the extent Y2K issues result in improper funding or payments, there may be a cause for legal action.

Premises Operations and Product Liability

A large number of classes have been identified in the manufacturing and service industries as having exposure to Y2K problems. The classes that made most lists include:

- Computer or peripheral equipment
- Drug stores
- Financial services (including stockbrokers)
- Sales, service or consulting organizations
- Ticket agencies
- Agriculture

All manufacturing companies will have some element of exposure, but those most affected will likely be in the computer industry. Manufacturers who produce embedded chips and microprocessors that failed may face a myriad of product liability claims.

The health industry depends on computers to help dispense medicines properly. Because of the large number of software packages used for this purpose, it appears inevitable that some portion of the industry will have to deal with drugs dispensed at the wrong times.

To the extent the financial services industry cannot transfer funds properly, losses will occur.

Sales and service industries will be looked upon to fill coverage gaps because they sold or used the equipment with flawed embedded chips. While in most cases this may stretch the coverage definitions, there will be a duty to defend.

Even ticket agencies may produce tickets with incorrect dates.

Agriculture will be affected because of automated feeding systems, automated crop irrigation systems and cold storage warehouses.

One coverage issue facing all industries will be data corruption or losses. Disputes will likely arise over whether data, currently considered an intangible, can be considered tangible property that can be damaged. Case law provides that property on magnetic tapes, not yet printed, is considered tangible property. There is conflicting case law, however, that data in circuits and wires are not yet tangible. As a result, many industry experts believe that more litigation will arise to decide these issues.

There also may be claims for corollary damage, even in cases where primary physical damage and bodily injury coverage does not exist. For example, fire damage to adjoining properties where the primary fire is not covered may trigger a liability claim.

Errors and Omissions

Errors and Omissions (E&O) insurance generally provides coverage for claims alleging errors and omissions by the insured parties with respect to named professional services they provide. Most industry experts expect many "you didn't tell me we didn't have coverage" allegations to trigger error and omissions claims. Computer professionals likely will seek coverage under their E&O policies for Y2K issues. This coverage will be particularly important for computer professionals offering services to make businesses Y2K compliant.

Even if no written contract exists, one may allege that reliance on an implied promise of performance was breached. For example a consulting actuarial firm, with responsibility to deliver regular quarterly reserve analyses, cannot deliver because of an internal system failure could face an alleged breach of the "covenant of good faith and fair dealing" implicit in every contract. These lawsuits can take the form of contract claims as well as professional E&O claims.

If a company decides to correct licensed software from a vendor, copyright infringement could occur. Software is normally licensed in such a manner that the vendors retain the copyright. Those licenses usually limit the actions the licensee can take with respect to the software. Therefore modifications without required consent could result in a claim by the licensing vendor against the licensee.

E&O specialists are attempting to limit exposure by introducing exclusionary endorsements, a strategy that could backfire if other defenses are limited as a result.

Directors and Officers

Directors and officers (D&O) liability insurance covers claims against corporate directors and officers for "wrongful acts." Many policies also cover securities claims made directly against the corporation. Such policies only cover claims made during the policy term.

D&O was not intended for the Y2K exposure, given the frequency and severity of these potential claims. As a result, D&O will be another source of litigation. To the extent coverage or lack of coverage is communicated before the event, there is opportunity to avoid litigation. Companies specializing in D&O are attempting to manage the risk by communicating their policy in advance, or charging an extra premium for an expressed coverage endorsement. As one insurer put it, "silence is not golden."

The technology/computer industries will be most susceptible to D&O claims given their haste to develop competitive products, perceived lack of attention to the Y2K problem and failure to support earlier versions of their product. One such case is already being heard (Caplan vs.Symantec Corp). The plaintiff is alleging breach of implied warranty for earlier versions of the defendant's anti-virus software. The plaintiff is trying to get the company to upgrade all prior versions of the software at no charge.

Further Litigation Impacting Y2K Decisions

Currently, two legal actions could limit or expand liability for Y2K losses. Both cases seek to draw from previous product liability case law to limit liabilities arising out of Y2K.

One case is Kumho Tire Company vs. Carmichael. The industry has filed amicus briefs with the U.S. Supreme Court. The briefs urge that technical standards for the admissibility of expert testimony on Y2K lawsuits be the same as those used for expert scientific testimony in product liability cases. The basis for this position is set in the 1993 Daubert vs. Merrell Dow Pharmaceutical case where the Supreme Court imposed a number of restraints barring so called "junk science" from the courtroom in the litigation of an anti-nausea drug. This case law calls for federal judges to screen the reasoning and methodology of expert testimony before it can be heard, and also calls for this decision being made at the district court level rather than the appellate court level.

The other legal action is a Massachusetts case in which Arthur Anderson is seeking a declaratory judgment that it should not be liable for the cost of replacing a computer installed in 1989 at a customer site that was not Y2K compliant. Anderson's arguments center on the so-called state-of-the-art defense, i.e. if a defendant can show that it provided goods and services in accordance with the scientific knowledge available at the time of delivery, then the defendant complied with government or industry standards and is therefore not liable.

These cases are extremely important because they give courts an opportunity to define the boundaries of legal actions that can be taken in the wake of Y2K computer losses.

Future litigation also may arise between insurers and their reinsurers as they try to mediate coverage disputes between policyholders and their insurers. Some insurers may try to treat all of their Y2K claims as a single event so they incur only one retention before reinsurance coverage is triggered. Reinsurers, however, may fight this approach if the claims presented as a single event are not related.

In fact, the actual indemnity cost may pale in comparison to the legal costs of litigating Y2K coverage issues. One consulting group estimates that as much as $1 trillion will be spent to litigate Y2K problems.

Non – System Internal Issues

Two additional issues that will impact the financial well being of an insurer are (1) reinsurance negotiations in 1999 with the primary company and (2) asset and liquidity problems.

Reinsurance

As a result of uncertainties associated with Y2K coverages, the 1999 reinsurance renewal season may go a little slower then normal. Most reinsurers will likely look carefully at each company they underwrite to be sure its doing a good job in underwriting its own book of business. In addition, insurers will seek clarification on whether an occurrence, such as Y2K, can be considered as one event. Regardless of an insurer's approach to Y2K claims, they have a duty to defend suits against policyholders. That cost can be high, and the issue will be subject to continuous evaluation.

The larger reinsurers already have surveyed their larger clients regarding Y2K exposure. Most will follow the fortunes of their clients. There are notable exceptions where the company has high concentrations in lines where severity and frequency of claims are expected to be high. One insurer seeing an opportunity wanted to market a Y2K policy. After being rebuked by its lead reinsurer, the company decided to back off.

Asset and Liquidity Issues

Today's investment markets are so intertwined globally that an unprepared third world market could upset the whole trading network. To a lesser extent, individual bank transactions could tie up cash flow and it may become necessary to convert assets to keep the liquidity to pay claims timely. Insurers need to be aware of potential cash flow problems and plan accordingly. Insurers also are concerned about agents' balances. Some even contemplate increased use of lock-boxes for their producers.

Given the extent and potential of the Y2K phenomenon, it is obvious why the public sector is so interested in the steps being taken to minimize economic loss

Part 2 – The Department's Approach to Assessing the Y2K Preparedness of the Insurance Industry Operating in Texas

The Department developed its own business plan for analysis and responding to the preparedness of the insurance industry operating in Texas. It involved surveying all insurance entities operating in Texas, assessing the results and taking action on those entities that have failed to plan or prepare adequately for Y2K.

The Department hired the University of North Texas to collect the data and to merge the survey results with each company's financial data. A separate Analysis Task Force scored companies based on survey results and financial strength. As regulators, it is necessary to assess the loss potential for those companies that provide coverage for bodily injury and property damage. A similar assessment was done for third party liability exposure, particularly corporate officers and directors liability for acts or failures to act on the corporation's behalf, and errors and omissions for professionals providing Y2K services.

The process of conducting a Y2K assessment was complicated by the fact that systems may pre-date current company, resulting in awareness problems. Also, little or no actuarial data is available on possible exposure for damages covered by general liability, officers and directors and errors and omissions policies is available. What data there were still resulted in highly speculative estimates.

During this phase, Department staff sought more Y2K information through seminars, articles, vendor presentations and talking with large insurers about their Y2K efforts. Through this process, the Department began to identify potential resources for remediating systems or reinsuring companies that might be placed under regulatory control for lack of Y2K compliance.

The Survey

In early 1997, the Department became increasingly aware that some insurance entities might not be adequately preparing for the change in the millennium. Because no information database existed to examine the problem or its potential, a detailed forty-four question, multi-part survey was designed and administered as a special examination to almost 3,400 licensed insurance entities. The survey was designed to:

- assess the company's internal systems, such as claims processing and accounting.
- identify each companies reliance in external vendors or service providers and the extent to which due diligence had been conducted by these entities.
- determine the potential exposure for liabilities under policies issued for the property and casualty sector of the industry.

The survey was mailed in November, 1997. It was sent to individual companies rather than company groups because of a concern that companies within groups could have independent systems – particularly in today's merger/acquisition environment, and the Department's authority is at the company level, not the group level.

While the survey was directed to all companies doing business in Texas, the emphasis of this analysis will be on the P&C companies. A copy of the survey is attached as Appendix 1.

The Systems Risk

Most insurers are computer dependent for policy entry, as well as claims coverage and settlement functions. Policy and claims systems can be as much as 30 years old and written in archaic computer languages, while others are state-of-the-art systems. Most are somewhere in-between.

A goal of the survey was to have each company identify its level of preparedness. To that end, questions were asked regarding platforms, software development and maintenance systems and, if applicable, service providers and other business partners.

The Insured Exposure Risk

The interest of the regulator is similar to that of an insurer. Both need to know if claims arising from Y2K, perhaps never anticipated in the underlying rates of the policies, could impair the insurer's financial well being and its ability to make future claims payments. While recognizing it was not possible to identify the specific sources of exposure within a company, general questions were asked regarding current premium writings and policies in force by line and, in the case of commercial P&C business, classes of business written.

The survey went further by including an actuarial estimate section to quantify Y2K risk. Without historical data, such estimates were likely to be no more than informed judgements, but such estimates could have provided some basis for determining possible Y2K losses if patterns emerged.

Setup of the Survey

The 7-page survey helped profile the company by asking for the current policies-in-force count and the premium percentage breakdown by major line. For P&C companies that write commercial lines, additional classification information was required. A second set of questions explored each company's commitment to addressing the Y2K problem, while a third section addressed system readiness. The fourth section questioned the extent the company had checked the Y2K status of producers, reinsurers and service providers. The fifth section questioned the type of exposures being written and what was being done to protect the company from the potential liability of existing contracts. The last section addressed the actuarial and accounting issues, particularly regarding extraordinary reserve adjustments.

The Responses

The response rate was 90 percent (92 percent for P&C companies). The survey was mandatory for all, so the other 10 percent were dealt with separately and not included in the data discussed here. The quality of responses was satisfactory in that most of the companies filled out the survey in full.

Response Rates by Company Type

Class Code	Total in Database	Responses	Response Rate
Fraternal	36	35	97%
Life & Health	868	810	93%
Multiple Welfare	9	7	78%
Property/Casualty	1049	965	92%
Specialty	1397	1193	85%
Title	24	22	92%
Total	3383	3032	90%

The NAIC database provided each company's financial information.

Initial Analysis of Systems Readiness

The first analysis of the data revealed that 23.0 percent of the insurance companies had a Y2K plan, but not written; 3.3 percent did not yet have a plan; and 5.4 percent did not feel they needed to address the issue. The remaining 68.3 percent had written plans.

Regarding the readiness of companies the respondents reported as follows:
- 7.5% will be 100% prepared by 12/31/97,
- 59.7% will be 100% prepared by 12/31/98,
- 96.5% will be 100% prepared by 12/31/99.

Regarding the question of how the company would become Y2K compliant, the survey showed that companies were using a variety of methods to get ready:

- 68.6% of the companies anticipated using external consultants,
- 57.8% were replacing hardware,
- 61.1% were replacing operating systems,
- 70.3% were replacing application software,
- 80.4% were fixing application software.

More than 50 percent of the companies had no backup plan in case their Y2K efforts failed. Of those with backup plans, more than 50 percent involved manual policy processing.

More than 97 percent of the companies reported that financing for planning, execution, testing and maintenance would come from their current operating budgets.

More than 29 percent of the companies reported they did not include a provision for running software previously archived after 1/1/2000.

Systems testing questions showed that 44.0 percent of the companies were testing in a computer environment configured and operated as if it were after 12/31/99. Of the companies that had done testing approximately 50 percent had produced accurate results.

The following chart reflects the progress of companies planning to remediate their application software at the time of the survey.

Compliance Activities				
	Not Started	In Progress	Complete	Total
Plan Preparation	1.5%	32.9%	65.6%	100.0%
Execution	6.9%	82.7%	10.4%	100.0%
Testing	19.9%	73.8%	6.3%	100.0%
Maintaining	32.1%	61.1%	6.8%	100.0%

The Initial Scoring System

To begin the process of separating companies, a scoring system was developed by the Y2K Task Force, in conjunction with the Research Group, based on the survey results. Each company received a unique score that enabled the regulatory response to begin on a somewhat prioritized basis.

Four main risk factor groups were developed. The risk factors considered were:

- Systems/operations, regarding an entity's systems readiness,
- Insurance/claims, regarding how well an entity is prepared to deal with impacts of Y2K on its policyholders,
- Financial stability, based on financial information available to the Department; and exposure in risky lines, based on a property/casualty insurer's premiums for product liability, other liability, commercial multi-peril and boiler and machinery,
- Level of exposure to Texas policyholders, with efforts focused primarily on companies with material writings in Texas.

Risk Factor 1 – Systems Operation

Companies without a written plan immediately went into a special category for further research.

Other considerations in Risk Factor 1 were:

- Interim dates toward compliance,
- Backup plans if systems fail,

- Budget for Y2K,
- Source of funds to pay for Y2K preparedness,
- Leap year readiness,
- Level of testing at the time of the survey,
- Simulation testing.

The results were used as an internal sorting tool to determine the companies to investigate further.

Risk Factor 2 – Insurance Exposure

Points were assigned based on the responses to survey questions 2, 32-34, 38-41, 49.
The determining factors used to score exposure were:
- distribution by line,
- strategic business planning by line,
- use of Y2K exclusions,
- assessment of potential liability.

Once again the scoring system could not identify the companies with exposure, but could identify potential areas for further investigation.

Risk Factor 3 – Financial Stability

The Department assesses the financial stability of each company. This confidential information was the basis for Risk Factor 3.

Risk Factor 4 – Texas Exposure

Texas premium volume was used as the basis for Risk Factor 4, with companies writing over $35 million receiving the highest risk assessment. The purpose was to add an economic impact measure to the scoring.

Once the scoring took place, the results were sorted and ranked in various ways. These results, plus further discussions with staff analysts and the companies themselves dictated the level of initial regulatory attention given to a company.

Analysis of the Actuarial Responses

The survey concluded by asking about reserve adjustments being made as a result of anticipated Y2K claims. The few companies that reported these adjustments had no real support for their estimates and admitted that they were educated guesses based on limited knowledge of the exposure. The only pattern that emerged from the survey was that no estimates were possible.

However a corollary purpose was served to alert the P&C actuarial community to the Y2K situation. The actuary will be expected to make estimates of ultimate losses very early after the new year. Data will be immature and non-traditional methods will have to be used to make the evaluations. Several of the larger companies have indicated that they intend to employ methods similar to those used to estimate environmental liabilities. Until patterns emerge it appears frequency and severity estimates will be the best way to approach the problem.

Part 3 – Regulatory Action

The examination survey was the initial step in the Department's evaluation of the readiness of the insurance industry. Under its statutory authority, the Department then developed a strategy to respond to the Y2K challenge.

Use of Survey Results

Once the results of the survey were tabulated, the Task Force categorized companies in the following ways. Those companies that:

- did not responding to the survey,
- responded to the survey but indicated they did not have a written Y2K plan,
- responded to the survey but had responses indicating high-risk based on the Task Force's scoring system;
- responded to the survey and had responses indicating low-risk based on the Task Force's scoring system.

Non-Respondents

Companies that did not respond to the survey were presumed to be unprepared, and considered top priority because of the limited time to develop and implement a plan before the millennium change. The Department's regulatory response to these companies is described below, followed by discussions of the Department's regulatory response to those companies having Y2K plans and considered either high-risk or low-risk.

At any time, companies could move from one category to another, and the Department built in flexibility to allow for this movement. For example, some companies not responding to the initial survey or follow-up requests did provide a survey response in the Department's analysis phase, and these were entered into the system accordingly.

Companies were identified either as non-group or as part of a group of companies. If a company was part of a group of otherwise responding companies, analysis staff checked responses from the group as a whole to identify possible mis-routing of mail or other errors that could account for a single company in the group not responding. In the event of such an error, company management was offered the opportunity to send a completed survey to the Department, and the survey response was subjected to the same scoring process as original responses.

The first regulatory actions taken by the Department as a result of the survey were management conferences with non-group, actively writing insurance companies that did not respond to the survey. This was a relatively small number of companies. The conferences yielded a variety of findings, ranging from companies that were fully implementing a feasible and timely written plan to those that had no written plan at all. The first of these management conferences was held with a company at the latter end of the range, i.e., management did not have a written plan and timeline for becoming Y2K compliant. The Department moved quickly to place the company under administrative oversight to assist the company toward developing, evaluating and implementing a plan to become Y2K compliant.

By early design, the Department's approach to assessing the preparedness of the industry in Texas is evolving and flexible. As an example, Department staff learned from these initial management conferences that Department and company resources could be conserved by more in-depth initial conference calls with company management. Information gleaned from these calls determined the next course of Department action, which could include a request for a management conference, a request for a written Y2K plan, an onsite examination, or regulatory intervention. The Department has undertaken this approach for the remaining non-responding insurance companies which are those in a group for which no company in the group responded.

Respondents with No Written Y2K Plan

The Department considered the lack of a business plan to address Y2K as a reliable indicator that future examination was required. For the more than 1,250 companies that responded to the initial survey that they did not have a written plan, the Department sent follow-up letters asking company management to develop and provide a written plan. These letters included the specified required format for a plan, with general categories of the company's self-assessment, environmental assessment, mission-critical systems assessment, and specific details for each assessment category.

Companies indicating that they did not have a written plan were grouped for further analysis. Outside consultants were used to assist in this analysis and followed a standard Department procedure so as to assist in the evaluation of the more than 1,250 plans that were in this category. Companies were then prioritized based on evaluations of these plans and based on the type of company. Again, Department action regarding any company considered at high risk based on its written plan includes a request for a management conference, an onsite examination, or regulatory intervention such as administrative oversight or supervision.

Respondents Considered as High Risk based on Survey Response

The regulatory response toward insurers and other entities considered as high risk because of their survey responses is consistent with the regulatory response toward non-respondents and respondents with no written plan. This response also is consistent with the Commissioner's statutory authority. Department action may include a request for management conference, an onsite examination, or regulatory intervention such as administrative oversight, supervision, or conservation under the direction of the Department's Conservator. These companies were prioritized on an economic impact basis. Wide use was made of the expertise in the Department regarding various companies, particularly the knowledge of the financial analysts and the examiners. Based on that prioritization, a number of company management teams have been invited to the Department for a conference regarding their Y2K status.

Respondents Considered as Low Risk based on Survey Response

The Department considers a company's management responsible for it's continued operations. If management's response to the survey indicated that the company was well prepared in regard to internal systems, external reliance, and policyholder protection, the Department does not anticipate further action, unless subsequent information becomes available that would indicate otherwise.

Going one step further, the Department examined many of the Y2K-ready larger companies to determine what the prudent insurance company should be doing to prepare for Y2K. These companies were very cooperative, and the following section is a compendium of what was learned in this review.

Part 4 – The Prudent Insurance Company

The research done to date has made it evident what prudent insurance companies should have done by now and what they need to do over the course of 1999. Presented in outline form, the hope is that this compilation will help in every company's self-assessment.

1. The company should appoint a Y2K coordinator.
2. A management team should be formed around the coordinator and meet regularly. The team should include as many disciplines as possible.
   - **Information Services** should have examined and corrected the company's own systems and be well into the testing phase. So they can understand all issues and communicate their timetables, particularly for integrated and simulation testing, they need to be part of any management group. They also need to be aware of special data needs.
   - **Underwriting and loss control** should identify Y2K exposure and advise the production force and policyholders of Y2K compliance issues.
   - **Legal** should pass on Y2K forms and endorsements and to work with Claims to identify and define what constitutes a Y2K claim.
   - **Claims** should develop a strategy and special training that will be necessary to identify and deal with Y2K claims. Most large companies are centralizing the handling of all Y2K liability claims because of their special nature and to assure a consistent approach.
   - **Financial and Accounting** should help management assess the cost of Y2K compliance and identify the balance sheet impact as claims are made.
   - **Actuarial** should have the background to determine ultimate losses, not only indemnity claims but also defense costs early in the process. As soon as Y2K

hits, management and regulators will want to know the financial impact of Y2K. To this end the actuary will need to have databases set up to identify Y2K claims in sufficient detail to make this assessment.

3. The management team should certify that agents and producers are compliant, as well as other key suppliers and customers' systems.
4. After plans and time lines are developed, the company should create an audit trail regarding the status of those plans. This may be very important if there are failures down the road.
5. The company should identify exposure to third party claims and determine if it is feasible to try and limit that exposure.
6. Management should determine what information needs to be reported to their Board of Directors regarding internal compliance as well as potential outside exposure.
7. Company managers should monitor what competitors are doing to become Y2K compliant.
8. Management should evaluate Y2K compliance as part of any merger/acquisition activity in which the company is engaging.
9. Contingency planning at all phases of Y2K should be developed in case remediation efforts fall short of expectations.

Conclusions and Future Direction

The overall regulatory objective is for every insurance entity to have its information systems ready. Regulators want to make sure that companies can continue to pay claims, accept premiums and issue policies. Also companies need to be sure that they can continue to pay providers and beneficiaries and report financial and statistical information to organizations that require the information. All insurers face these issues.

All firms will be have a certain duty of care to assure that they are Y2K compliant. As failures occur and liability can be alleged, property and casualty insurers will be exposed to claims under contract liability, errors and omissions and directors and officers policies. It is important for every insurer to know and understand the issues in advance to assure timely disposition of claims.

Cooperation and understanding on the part of everyone in the industry is required to maximize the effectiveness of Y2K efforts. The Department continues to be fully engaged in reviewing and responding to Y2K compliance and have committed significant resources to evaluate and help remediate companies in need of extra help. This challenge adds considerable layers of complexity to the already complex regulatory workload. To the extent necessary, staff has been augmented with outside experts. The Department is prepared to seek reinsurance for smaller books of business written by companies that have either lost their reinsurance coverage or have failed to underwrite their business to the satisfaction of their reinsurer

Y2K considerations may speed company consolidations and may cause serious strains on capital. While not suggesting an Armageddon type situation, the industry may find that cash flow to handle worst case scenarios is a problem because of the volume of claims reported in a very short time frame.

As the clock ticks, Y2K preparedness will become ever more critical, and due diligence will be the catchword for the industry. Insurers that are well prepared going into the 1999 policy renewal year are probably going to be fine. Those that are "in denial," however, may find themselves hit with a number of impacts such as exclusions by their reinsurers who could cause regulators to effect a run-off situation, or find a way to reinsure or merge a book of business. Timing is critical. By now, Y2K awareness has reached the height where there is no excuse for not having addressed the problem. The question remains: has it been addressed enough?

The problem is serious enough that federal legislation is being considered to provide companies that disclose Y2K remediation efforts with protection against lawsuits based on the fact that they have shared information. In addition, legislative bills are being considered to limit the liability for computer date failures. Only damages related to bodily injuries, costs reasonably incurred by claimants to reprogram or replace computer systems, and damages suffered through a breach of excess warranties would be recoverable.

In the end, regulators may be confronted with the possibility of companies incurring very high Y2K losses compared to relatively thin surplus levels. The effects of these losses will be felt well beyond the year 2000 and regulators will need to collect and analyze data regarding the frequency and severity of Y2K losses. To that end, regulators may be well served to include data reporting requirements in the Annual statement blank for the year 2000 and beyond.

Clearly, Y2K is a global problem, touching every aspect of the world economy. The insurance industry and the regulatory community must continue to act in full cooperation as we approach the millennium change.

Appendix 1

Company Profile

C P 1. How many in-force policies does your company have? Inside Texas ______________

Outside Texas ______________

C P 2. What is the breakdown of your policy distribution in terms of premium volume? (If your company is a *non-insurer*, answer in terms of *policies processed.*)

Insurance Products	Percentage of Distribution
Product liability	_____ %
Professional liability (including directors & officers, errors & omissions)	_____ %
All other commercial liability (including umbrella and commercial auto)	_____ %
Personal auto liability	_____ %
Personal property	_____ %
Business interruption	_____ %
Commercial fire and allied	_____ %
Other non-commercial liability	_____ %
Life annuity insurance	_____ %
Health and accident (including HMO, group health, etc.)	_____ %
Disability	_____ %
Title insurance	_____ %
Other ______________________________	_____ %
Total	100%

C P 3. Give us a breakdown of the businesses you insure (based on the number of policies) as of 9/30/97.

	0%	1 to 25%	26 to 50%	51 to 75%	76 to 100%
Agricultural	☐1	☐2	☐3	☐4	☐5
Mining	☐1	☐2	☐3	☐4	☐5
Construction	☐1	☐2	☐3	☐4	☐5
Manufacturing	☐1	☐2	☐3	☐4	☐5
Transportation	☐1	☐2	☐3	☐4	☐5

Finance	☐1	☐2	☐3	☐4	☐5
Health care related	☐1	☐2	☐3	☐4	☐5
Education	☐1	☐2	☐3	☐4	☐5
Retail	☐1	☐2	☐3	☐4	☐5
Professional services	☐1	☐2	☐3	☐4	☐5
Other services	☐1	☐2	☐3	☐4	☐5
Other	☐1	☐2	☐3	☐4	☐5

Planning and Budgeting For Year 2000 Compliance

"Year 2000" refers to the problem that automated systems could encounter on January 1, 2000. Computer systems that use a two-digit year may incorrectly register the year 2000 as "00." This could adversely affect numerous computer calculations and transactions that are date sensitive.

The definition of Year 2000 compliance has been heavily debated. For the purposes of this exam, Year 2000 compliance means that 20th and 21st Century date values will be processed correctly and that date-dependent calculations will produce accurate results.

C P 4. Does your company have an initiative to address Year 2000 issues?

☐1 Yes, a written plan
☐2 Yes, an unwritten plan only
☐3 Not Yet (skip to question 6)
☐4 Do not intend to address the issue (skip to question 24)

C P 5. (If yes to question 4) If your company has an initiative to address Year 2000 issues:

When was the plan adopted? _ _ / _ _ _ _ (month/year)
When will your systems be mostly compliant? _ _ / _ _ _ _ (month/year)
When is your project's anticipated completion date? _ _ / _ _ _ _ (month/year)

C P 6. Using an estimate, to what extent will your company be Year 2000 compliant by:

12/31/1997? ______ %
12/31/1998? ______ %
12/31/1999? ______ %

C P 7. How do you plan to become compliant? (check all that apply)

☐1 Using external consultants
☐2 Using internal staff
☐3 Replacing hardware
☐4 Replacing operating systems
☐5 Replacing application software
☐6 Fixing current application software
☐7 Not sure
☐8 Other ______________________

C P 8. Does your company have a plan to continue operations if it is not Year 2000 compliant by December 31, 1999, or if Year 2000 efforts fail?

Estimated Cost for One Year

☐1 Yes

☐1 Outsource processing outside of the affiliate group $ ____________

☐2 Parent company will process $ ____________
☐3 Manual processing $ ____________
☐4 Merger $ ____________
☐5 Sales of business $ ____________
☐6 Dissolve/terminate business $ ____________
☐7 Process at alternative site $ ____________
☐8 Other ____________________ $ ____________

☐2 No

C P 9. As of October 1997, what is the percentage of completeness in terms of labor hours spent?
_______ % (hours spent / budgeted hours)

C P 10. How much has or will your company budget for each phase of the Year 2000 project?

Total Number of Dedicated Dollars Labor Hrs Full Time Equivalents

Plan preparation/identify problem $ ____________ ____________

Plan execution/remediation $ ____________ ____________

Testing $ ____________ ____________

Maintaining Year 2000 compliance $ ____________ ____________

C P 11. How will your company finance its Year 2000 project? (Numbers should add to 100% across)

Activity	Source of Funding			
Planning	☐1 Current operating funds___%	☐2 Allocated/Reserved ___%	Surplus ☐3 Other ___%	
Execution	☐1 Current operating funds___%	☐2 Allocated/Reserved ___%	Surplus ☐3 Other ___%	
Testing	☐1 Current operating funds___%	☐2 Allocated/Reserved ___%	Surplus ☐3 Other ___%	
Maintenance	☐1 Current operating funds___%	☐2 Allocated/Reserved ___%	Surplus ☐3 Other ___%	

C P 12. If you indicated "other" sources of funding for planning, execution, testing or maintenance, please describe those sources: ____

C P 13. Approximately, how many lines of computer code does your company plan to change as part of the Year 2000 project? ________________

Internal Preparation for Year 2000

C P 14. For your main line of business (based on premium revenue), provide the date you issued or plan to issue policies with expiration dates after 12/31/1999: _ _ / _ _ _ _ (month/year)

C P 15. After 1/1/2000, does your Year 2000 plan provide a way to **access data** and **run software** that was previously archived (going back to at least 1/1/1995)?

Access data ☐1 Yes ☐2 No

Run software ☐1 Yes ☐2 No

C P 16. Does your Year 2000 project take into account that the year 2000 is a leap year?
☐1 Yes ☐2 No

C P 17. Have you tested your systems for activities which cross the year 2000 boundary?
☐1 Yes ☐2 No

C P 18. **If yes**, what did the tests show?

- ☐₁ All systems produce accurate results
- ☐₂ Most systems produce accurate results
- ☐₃ A few systems produce accurate results
- ☐₄ No systems produce accurate results

C P 19. When testing for Year 2000 compliance, what portion of testing occurs in a computer environment that is configured and operated as though it were after 12/31/1999? (i.e. on a machine that has a date at or beyond the year 2000) ☐₁ All ☐₂ Some ☐₃ None

C P 20. What is the **format of your current**, most common year representation in your date definition? (Example: mm/dd/yyyy would be a four-digit representation)

☐₁ four digits ☐₃ two digits ☐₅ 1/2 byte of a date field to indicate century
☐₂ three digits ☐₄ one digit

C P 21. When compliant, what **will be the format** of your most common year representation in your date definition? (Example: mm/dd/yyyy would be a four-digit representation)

☐₁ four digits ☐₃ two digits ☐₅ 1/2 byte of a date field to indicate century
☐₂ three digits ☐₄ one digit

C P 22. When the Year 2000 project is complete, will your on-line screens display a 4-digit year?

☐₁ All ☐₂ Some ☐₃ None

C P 23. If you plan to remediate your application software, which of the following compliance activities are in progress or have been conducted?

Not Started - or -	In Progress - or -	Complete	Phase
☐₁	☐₂	☐₃	Plan preparation/identify problem
☐₁	☐₂	☐₃	Plan execution/remediation
☐₁	☐₂	☐₃	Testing
☐₁	☐₂	☐₃	Maintaining Year 2000 compliance

C P 24. Please rank the most prevalent methods by which your company's information systems are maintained (with "1" being the most prevalent, "2" two being second most prevalent, etc.).

___ Internal IS department (staff)
___ Facilities manager/outsourced
___ Remote user (no in-house systems)
___ Other ______________

C P 25. Which of the following core platforms does your company operate? (check all that apply)

- ☐1 IBM Mainframe computers
- ☐2 Non-IBM Mainframe computers (Please specify brand ______________________)
- ☐3 Mid-range computers (such as Sequent, Dec Alpha's, AS-400, SunSparc Station . . .)
- ☐4 Personal computers (PC's)
- ☐5 Client Server environment
- ☐9 None of the above

C P 26. What are the primary operating systems (such as DOS, VM, Unix, OS 400, Windows NT), database programs and application software programs involved in running the **premiums** and **claims** systems on your core platforms?

	Version	Vendor	Computer Platform 1 Mainframe 2 Mid-range 3 PC	System is Year 2000 Compliant	Access to source code
Operating Systems					
Premium System			☐1 MF ☐2 MR ☐3 PC	☐1 Yes ☐2 No	☐1 Yes ☐2 No
Claims System			☐1 MF ☐2 MR ☐3 PC	☐1 Yes ☐2 No	☐1 Yes ☐2 No
Application Software					
Premium System			☐1 MF ☐2 MR ☐3 PC	☐1 Yes ☐2 No	☐1 Yes ☐2 No
Claims System			☐1 MF ☐2 MR ☐3 PC	☐1 Yes ☐2 No	☐1 Yes ☐2 No

C P 27. When considering all the premiums and claims application software in which you have access to source code, what is the source code distribution across all applications?

Language	Number of lines of code	Percent of total	Comments
COBOL			
RPG			
ALC			
C++			

Visual Basic			
PLI			
4GL (specify)			
Other (specify)			
Total		100%	

C P 28. Are your telephone systems Year 2000 compliant? □1 Yes □2 No

C P 29. Does your Year 2000 plan consider the impact of date sensitive embedded chips and the effect that failures in the chips can have on operations (i.e. HVAC, elevators, security systems)? □1 Yes □2 No

Business Partners

C P 30. Does the Year 2000 plan consider Year 2000 compliance of significant business partners?

□1 Yes □2 No

C P 31. What portion of your contracts emphasize that business partners are Year 2000 compliant?

□1 All □2 Some □3 None

P **32. What is the status of Year 2000 compliance for the following business partners? Does your company conduct electronic data transfers with any of the following? Have or will you test partners for compliance?**

Business Partner	How many of these partners are compliant?				Elec. Data Transfers	Testing for Complianc
Reinsurers	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
Reinsurance intermediaries	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
Asset managers	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
Agents/producers	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
MGAs / TPAs	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
Affiliates (within same group)	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No
Service providers	□1 All	□2 Some	□3 None	□9 Don't Know	□1 Yes □2 No	□1 Yes □2 No

Information systems	☐1 All	☐2 Some	☐3 None	☐9 Don't Know	☐1 Yes ☐2 No	☐1 Yes ☐2 No
Telecommunications	☐1 All	☐2 Some	☐3 None	☐9 Don't Know	☐1 Yes ☐2 No	☐1 Yes ☐2 No

Strategic Business Planning

C P 33. For each of the following lines, please estimate the **percentage of your current policies** in which the following conditions apply:

- Losses associated with the Year 2000 problem may be covered;
- Losses associated with the Year 2000 problem are specifically excluded;
- If significant claims associated with the Year 2000 problem are likely or unlikely.

Insurance Products	Losses associated with the Year 2000 problem may be covered					Losses associated with Year 2000 problem are specifically excluded					Likelihood of significant claims	
	0%	1 to 25%	26 to 50%	51 to 75%	76 to 100%	0%	1 to 25%	26 to 50%	51 to 75%	76 to 100%	Likely	Unlikely
Product liability	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5	☐1	☐2
Professional liability	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5	☐1	☐2
All other commercial liability	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5	☐1	☐2
Business interruption	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5	☐1	☐2
Other insurance products	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5	☐1	☐2

C P 34. Does your company have plans to exclude Year 2000 coverage on future policies?

☐1 Yes (What type of policies? ______________________________)

☐2 No

C P 35. (If yes to 34) What is the most common **effective date** of policies that will exclude Year 2000 coverage? (month/year) _ _ /_ _ _ _

C P 36. Will Year 2000 buy-back options (endorsements or riders to offer specific Year 2000 coverage) be available? ☐1 Yes ☐2 No

C P 37. Literature suggests that many Year 2000 problems will be caused by failures in date-sensitive embedded chip technology. Please provide a rough estimate of the **percentage of your current policyholders** that either manufacture, sell, service or use high-tech products with date-sensitive embedded microprocessors (percentages will most likely *not* add to 100%):

Manufacture _____% Sell _____% Service _____% Use _____%

Actuarial Estimates

In calculating answers for questions 38 through 42, have your actuaries consider the impact of your policyholders' Year 2000 non-compliance that may result in:

- Claims resulting from failures of embedded chip technology found in elevators, escalators, aircraft, home heating/cooling systems, home security systems, home appliances, automobiles, medical equipment, banking equipment, computers, telephone systems, etc.
- Business interruption claims
- Errors and omissions claims
- Product liability claims
- Claims against directors and officers
- Claims from exposure in use, sales, manufacture, and servicing of high-tech products

C P 38. Have you assessed the costs that your company may incur resulting from legal defense as a result of Year 2000 issues? ☐₁ Yes ☐₂ No

C P 39. **If yes**, how would you rate the impact of exposure upon your company's surplus?

☐₁ Little or no impact ☐₂ Some impact ☐₃ Significant impact

C P 40. Have you made an assessment of the impact of business failures among non-compliant **policyholders** due to the Year 2000 problem? ☐₁ Yes ☐₂ No

C P 41. **If yes**, how would you rate the impact of policy holder business failure on your surplus?

☐₁ Little or no impact ☐₂ Some impact ☐₃ Significant impact

C P 42. Estimate the maximum theoretical amount of loss for your company due to Year 2000 events:

$ ____________

C P 43. What percentage of the amount in question 42 is reinsured outside your affiliate group? _____%

C P 44. What percentage of the theoretical loss amount in question 42 is in Texas? ________%

C P 45. In anticipation of potential claims resulting from Year 2000 events, will your company make adjustments to the following?

	1998 Budget Year		1999 Budget Year		2000 Budget Year	
	Adjustment	$ Amount	Adjustment	$ Amount	Adjustment	$ Amount
Surplus:	☐₁ Increase ☐₂ Decrease ☐₃ No	$	☐₁ Increase ☐₂ Decrease ☐₃ No change	$	☐₁ Increase ☐₂ Decrease ☐₃ No	$

	change				change	
Reserves:	☐1 Increase ☐2 Decrease ☐3 No change	$ ______	☐1 Increase ☐2 Decrease ☐3 No change	$ ______	☐1 Increase ☐2 Decrease ☐3 No change	$ ______
Premiums:	☐1 Increase ☐2 Decrease ☐3 No change	$ ______	☐1 Increase ☐2 Decrease ☐3 No change	$ ______	☐1 Increase ☐2 Decrease ☐3 No change	$ ______

On Hierarchy of Actuarial Objects: Data Processing from the Actuarial Point of View

Aleksey S. Popelyukhin, Ph.D.

On Hierarchy of Actuarial Objects:

Data Processing from the Actuarial Point of View

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Introduction

Like all professionals in the information era, actuaries need computers to automate non-creative activities and to relieve them from the burden of repetitive actions.

Actuaries need a system which shields them from the complexities of computer architecture and provides an abstraction and generalization exactly at the level of the common denominator of all actuarial functions.

From the actuarial point of view, an ideal data processing solution is a (a) transparent to users (b) highly efficient (c) storage/retrieval system for (d) structured actuarial data (objects) with (e) an extremely flexible (f) computationally complete (g) open (h) calculation engine. In short, a system which speaks actuarial language and makes it very easy to express actuarial algorithms and very hard to make mistakes. The paradigm where goals of abstraction, flexibility, simplicity and reliability can easily be achieved is the Object-Oriented (OO) model.

In order to "teach" an object-oriented data processing system to "speak actuarese" actuaries need to structure and categorize their data as well as formalize their algorithms. A well-defined hierarchy of actuarial objects creates an environment for the effortless expression of actuarial business rules and algorithms.

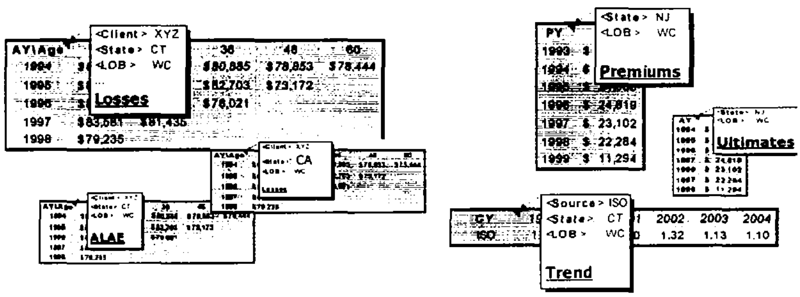


Figure 1

To perform their professional duties, actuaries operate with chunks of structured data, each chunk with its own set of properties (see Figure 1.) Some properties (line of business, location) help to distinguish one chunk of data from another, while other properties (loss vs. ALAE, dollars vs. counts) describe "actuarial nature" of the data and help determine which actuarial operation is appropriate to perform on them. It is intuitively clear that different kinds of properties differ in their origin and their effects on actuarial calculations. It is also immediately apparent that proper use of these properties in the actuarial data processing system may significantly increase the system's effectiveness and significantly reduce mismatch between data chunks and the algorithms applied to them. Let us formalize these findings and make evident that the distinction between different kinds of properties lies as deep and is as fundamental as the difference between *object* categorization and *class* hierarchy in an object-oriented model. Let us also demonstrate how this knowledge can be communicated to OO system designers and used to build effective and reliable actuarial data processing solutions.

Object Orientation[*]

Object Orientation is a preferable paradigm for

- *real world modeling*
- *creation of reusable, extendable and maintainable software components*
- *construction of reliable and consistent applications*

The OO paradigm facilitates communication between the user/actuary and the system designer. For example, compare the same calculation expressed in spreadsheet syntax and in OO fashion.

`=(sum(C35:C39)-max(C35:C39)-min(C35:C39))/3` ***(Spreadsheet)***

`AgeToAgeFactors.Average(Type:=ExclHiLo, LastDiagonals:=5)` ***(OO)***

Figure 2

The former expression does not communicate to the user the purpose of calculation, and is prone to errors. Nor is it the best possible algorithm: indeed, it requires 3 passes through the array C35:C39 (for `sum`, `max` and `min`) instead of single pass. On the other hand, as latter expression demonstrates, OO approach creates an intuitive environment for the user (when he needs an average, he just requests so) and leaves the freedom of implementation to the system designer. When an algorithm gets updated due to improvements or error corrections, user's code remains intact contributing to consistent and self-documenting actuarial application.

In a properly designed OO application, the only way to manipulate the data encapsulated within the object is by calling methods of (sending messages to) that object. Not only does such an approach protect data, maintaining the whole data structure in-sync, it also contributes to

- *Reusability: all the code needed to manipulate the data is contained in a detachable module.*
- *Maintainability and extensibility: all fixes and improvements can be made in a very localized place.*

---

[*] An excellent introduction to OO concepts and methods can be found in [1]. Martin [2] in a highly conceptual fashion discusses the theoretical foundation of OO technology, while [3] - [5] fully cover subject of OO databases.

- *Usability: hiding implementation of the methods and complexity of the data structure, the OO design provides means for proper and effective use of objects.*

The central notion in the object-oriented model is (surprise!) an object* – an entity, which contains both structured data elements (properties/attributes) and code (methods/operations) - for manipulations with the data. A set of objects with the same structure and behavior is declared and implemented through classes. Class contains both the description of the data structure and implementation of the methods. Thus, class is implementation of the object, while object is an instance of the class.

In order to model complexity of real life objects and variety of their relationships, OO approach relies on

- *encapsulation (data hiding and abstraction),*
- *inheritance (likeliness) and*
- *polymorphism (overloading)*

Encapsulation is a mechanism of binding data and operations on that data into single entity. One cannot access encapsulated data directly – all the manipulations on the data are done exclusively through operations associated with the data. Encapsulation, as a way to hide (and, thus, protect) data and privatize (and, thus, abstract) implementation of the object's behavior, shields the user from the object's internal complexity and allows operations with objects as whole entities rather than fractional structures.

Inheritance is a mechanism that facilitates the reuse of the program code from class to its ascendants (subclasses). Through this "class-subclass" relationship, inheritance naturally imposes a hierarchical structure on the collection of the classes. Inheritance, as a way to model "is like" relationship between objects, provides users with the ability to express structure and behavior of complex objects through the simpler ones and, on the other hand, reuse the code and derive new objects from the existing ones.

Polymorphism is a mechanism for declaring multiple operations with same name applicable to arguments of different types. Polymorphism models our real life ability to notice similarities between actions on different types of objects and our desire to use the same verb to name these actions. Polymorphism, as a way to apply the same operation to different classes of objects, contributes heavily to the generalization of algorithms and, thus, helps to avoid unnecessary repetition and duplication of errors.

> Example 1. For illustration, let's consider an actuarial triangle as an object. A triangle is the most intriguing actuarial object and the quality of its implementation may greatly affect the effectiveness of the whole actuarial system. Let's start with the storage structure. While it is most intuitive to store elements of the triangle as cells of the encompassing two-dimensional matrix, it may be not the best approach: first of all, almost half of the storage space would be wasted on empty cells and, secondly, not

* Authors of different books on OO subjects define major OO terms somewhat differently. "Object technology has its own vocabulary, which is *large* and *complex*. In its present state, it is unfortunately also *inconsistent*" (see [6]). For precision we cite exact definitions from [6] in the Glossary section.

every computer language and development environment supports variable size (dynamic) 2-D arrays. The most economical way to store a triangle would be Cantor-inspired enumeration of its elements into one-dimensional array (see Figure 3.) :

element (i, j) of the triangle maps into element $k = (i + j - 2)(i + j - 1)/2 + i$ *of the 1-D array*[*]

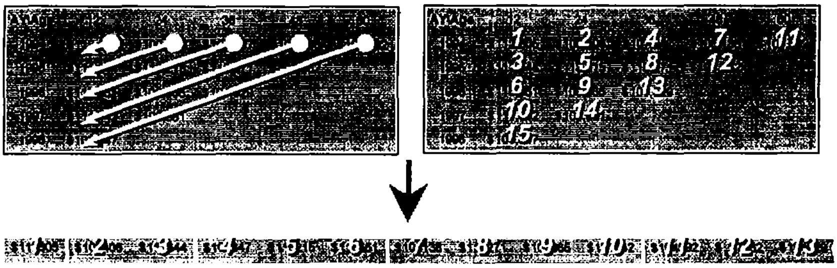


Figure 3

Not only does such a technique yield the most space-conscious arrangement of triangle's elements, it also provides an opportunity to place a whole triangle as a single record in the database, and it makes appending (and extraction) of the last diagonal as trivial as adding (reading) several consecutive elements at the end of the array.

Thanks to encapsulation, as long as in response for the message "RetriveTriangle" our object will return a familiarly looking half-empty matrix, user won't notice that elements of the triangle are stored in somewhat unusual way. Thanks to inheritance, we may derive different classes of triangles (like those with missing first diagonals, or those with only integer elements for representing "counts") without rewriting mapping formulas. And thanks to polymorphism, we may need to implement some basic manipulations on the triangles (like addition or trending) only once despite the existence of several different classes of triangles.

The natural desire to store objects in some organized fashion triggered the development of OO Databases. OO Databases introduced such fundamental notions as Persistence and Identity.

Persistence refers to availability of the objects across executions. Unlike temporary variables in the computer memory, persistent objects do not disappear when the program stops – they are stored for the future access.

Identity is a mechanism for distinguishing objects and a guarantee for their uniqueness. To insure uniqueness OO databases rely on the object identifiers (OID.) – values, which are unique, permanent and indifferent to the properties of the object. A good example of OID is a Social Security Number: it is unique, permanent and indifferent to the owner – one cannot describe a person looking just at SSN. In real life, however, we do not use an OID for identifying an object,

[*] For "non-isosceles" triangles k =`ceil` ((i**slope* + j – *slope* – 1)(i**slope* + j – 1)/(2**slope*)), where *slope* is the ratio of interval between rows over interval between columns and `ceil`(*a*) is a minimal integer not smaller than *a*.

rather we use a list of properties to describe the object we want – e.g., name, age and address which are properties of the "person" object and the most used identifiers, but not a person's OID.

Object Categories

No system can be called object-oriented unless it supports data encapsulation, inheritance and polymorphism. OO databases add requirements for object persistency and identity. Inheritance and polymorphism call for *class* ("internal") hierarchy, while the identity required by an OO database calls for *object* ("external") hierarchy!

Every insurance/re-insurance company has amassed a set of actuarial data arrays (triangles, rows, columns, diagonals, etc.) and preferred actuarial analysis techniques. Availability of established sets of actuarial categories and algorithms both simplifies and complicates OO Analysis and OO Design procedures for the OO actuarial data processing system. Simplification comes from the fact that most of the existing categories can probably be reused in the OO hierarchy and many of the algorithms can probably be wrapped into OO functional classes. Complications arise when OO Design requirements demand new categories to be introduced (or existing ones to be reshuffled) and algorithms to be adapted for the newly established object classification.

Every time an actuary attempts to tell apart different data arrays he has to introduce a (or use an existing) category with members describing these data arrays properties. Any distinction, which contributes to the criteria of identity (i.e., every property, which helps to distinguish one data array from others), generates new category or new member of an existing category. Category/member structure applied to the universe of all data arrays is called classification.

It is crucial to realize that an existing data array can be considered as the data portion of an actuarial object, and that an object also may store (among other things) information about what member of which category this object is. In essence, one can think of an actuarial object as a matrix with genealogy, or even simpler, "a triangle, who knows who he is" (see Figure 4.)

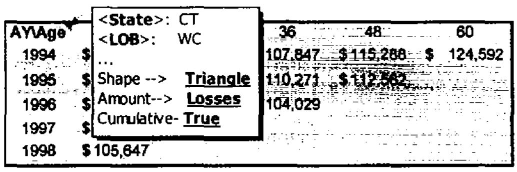


Figure 4

Not all categories were created equal. While some categories reflect an "actuarial nature" of the object, others are used just to distinguish similar objects of the same "nature".

There are 4 major kinds of categories:

1. *Those which define an object's place in a class hierarchy (class attributes)*
2. *Those which define an object's state*
3. *Those which serve identification purposes (dimensions*)*
4. *Those used for grouping within dimension (generations)*

A good example of the 1st kind of category would be "Shape." Indeed, members of this category belong to different classes, possibly inherited one from another: a Triangle (a member of this category) is a Matrix (another member) with half of the cells being empty and some additional specific functionality discussed below, a Diagonal (one more member) is a Triangle with even more empty cells and some more specific functionality, etc... A category "AccumulationType" would perfectly illustrate the 2nd kind of categories: members of this category (Cumulative, Incremental) define an object's state. "Line of Business" and "Location" are primary examples of the 3rd kind of categories, while "Groups of LOB's" and "Regions" with members like "All Liabilty", "All Property", "NorthEast" and "SouthWest" perfectly represent the 4th kind of categories.

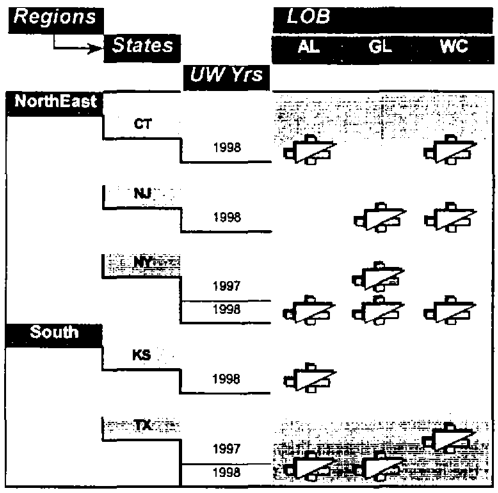


Figure 5

Categories of the first two kinds affect the way calculations are performed on the object's data, and thus affect object behavior; they reflect the inner actuarial "nature" of the object and in that sense they belong to the "internal" hierarchy. The remaining categories are imposed by the database requirement, which calls for every object to be uniquely identified; they describe an

* See Figure 5. For precise definitions of *dimensions, generations* and *members of dimension* see Glossary.

object and affect the structure of the external (relative to the object) entity - an OO database - and in that sense they belong to "external" hierarchy.

To summarize, classification of the *objects* (within a class) serves two main purposes: identification and selection in OO database, while *generations* provide convenient means for grouping. This is significantly different from the purposes of the *class* hierarchy, which defines inheritance and affects behavior of the objects.

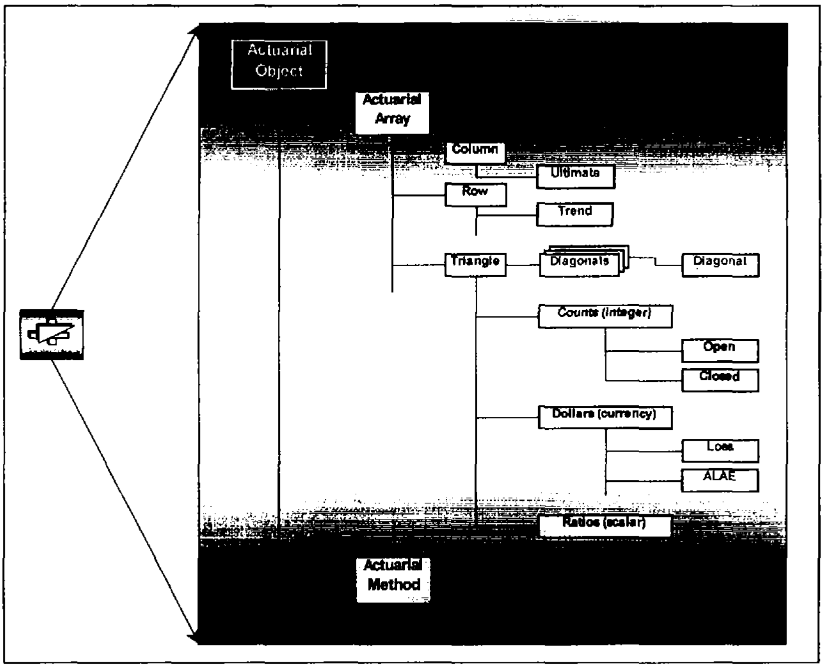


Figure 6[*]

The internal hierarchy includes categories which affect and are affected by the algorithms. The external hierarchy is the set of all objects factorized by internal hierarchy. Factorization is similar to packing items into the bags: each bag may contain several items, possibly, with their own classification, but factorization helps to classify bags themselves, ignoring what's inside (see Figures 5-6).

To build an OO data processing system, actuaries, during the OO Analysis stage of development, have to clearly define and segregate all 4 kinds of categories. It is important to realize that a

[*] There exist many different notations for expressing relationships between classes: Booch, Rumbaugh, OMT and, most notably, Universal Modeling Language UML (see [7], [8]). But for Figure 6 we used none of them, because Figs. 5-6 illustrate the notion of factorization rather than a particular OO design.

decision to place a category into an internal or external category will deeply affect the architecture and functionality of the resulting OO system. There is no single recipe for all companies: the same category could be internal in one company, external in another one and not exist at all in the third one. What is true for every company, however, is the fact that the classification can not be designed separately from the algorithms collection!

1st rule of thumb. To determine which hierarchy (internal or external) an actuarial category belongs to, one should take into account the following considerations:

- *(a) whether or not different members of this category need different algorithms to process them ("Counts" and "Dollars" as members of the "Amounts" category usually need different algorithms, while "NY," "NJ" and "CT" as members of the "Location" category are usually treated the same way),*
- *(b) whether or not different members of this category affect the way algorithms are applied (the "Cumulative" and "Incremental" members of the "AccumulationType" category require somewhat different calculations),*
- *(c) whether or not members of the category are used to define groups for possible aggregation into subtotals (the "NorthEast region" and "SouthWest region" members of "Regions" category can be defined through the groups of members from another category "Locations" and they do not serve identification purposes directly).*

Categories for external hierarchy should be defined in such a way, that two main activities – selection and aggregation (grouping) – be optimized. This approach may help to eliminate unnecessary levels in the hierarchy. If there is no intent to summarize amounts (data or results) across the members of a particular category, it may be blended with other categories, thus simplifying hierarchy. For example, the categories "Line of business" and "Sub-line" can be combined for something like {"Fire", "WC Med", "WC Ind", "GL BI", "GL PD"}. However, if category members simplify the selection process, then a category should be created. For example, category "DAC" with members {"Direct", "Assumed", "Ceded"} may significantly simplify selection of objects for "Gross vs. Net" actuarial analysis.

Another consideration for determining categories serving as dimensions in an external hierarchy is density. A multi-dimensional array is dense (as opposed to sparse) if a relatively high percentage of the possible combinations of its dimension members contain data values. Some categories may be combined in order to avoid impossible combinations of its members. For example, if only few lines of business have tail coverage, it make perfect sense to combine the "Line of Business" category with the "Tail Indicator" category (unless, of course, there are special algorithms for processing lines with tail coverages: in that case the "Tail Indicator" category belongs to internal hierarchy).

The analogy with currently available actuarial systems lies in the fact that sets of existing spreadsheets (different for different data types) are roughly equivalent to the categories of the 1st kind; parts of the labels/descriptions for the ranges in these spreadsheets approximate categories of the 2nd kind; some of the fields in the existing actuarial database almost correspond to the categories of the 3rd kind; and groupings of items in the summary of results affect selection of the categories of the 4th kind.

Implementation Issues

All OO theory can be irrelevant if one cannot implement or emulate an actuarial data processing system as an Object-Oriented application. Fortunately, it is not only possible, but it has been already done: there exist several OO actuarial systems, including a few designed and implemented by the author.

Possible approaches to the design of such a system may include the following major tasks:

- *actuarial data arrays can be implemented as a hierarchy of abstract data types*
- *actuarial methods can be wrapped into functional classes*
- *persistence can be achieved by storing objects in an Object-Oriented (or Object-Relational or just plain Relational) Database*
- *links to Actuarial Data Mart can be added to import object's data and to export results of analysis ([9])*
- *a flexible user interface can be added to finalize construction of the OO actuarial system*

Classes in OO application may have different behavior and thus can be used for different purposes. Classes with the principal responsibility of maintaining data information are called abstract data types or data managers. Classes with the principal responsibility of assisting in the execution of complex tasks called functional classes or facilitators. The distinction between abstract data types and functional classes is somewhat similar to the distinction between nouns and verbs in a sentence.

An abstract data type is a logical extension of a programming language's built-in data types (integer, boolean, character) with a clear separation of the external interface and internal implementation. Abstract data type is a class dedicated to the representation of the complex data structures along with necessary additional functionality for storage, retrieval and transformation of the data. A good example of an abstract data type would be "Date": it does not matter how "Date" is stored in that class as long as users have an ability to request date to be displayed in any given format, retrieve year, month or day and perform date arithmetic.

Functional class is a natural extension of the programming language's built-in functions and operators. Packing several functions, associated with some kind of real-life activity, along with shared data, functional classes can be compiled into active components sometimes called engines. Good examples of functional classes would be the simulation engine of "@Risk", the optimization engine of "Solver" and the calculation engine of "Excel".

If triangles (rows, columns and diagonals) are essentially data manager classes, that is, abstract data types, then encapsulated actuarial algorithms (actuarial methods) are functional classes.

2^{nd} rule of thumb. To decide which actuarial operation belongs to the data manager class (i.e., has to be implemented as a method in the abstract data type) vs. functional class, one should consider the following aspects of the algorithm:

- *(a) whether or not the algorithm is subject to future modification (always the same "accumulation of the triangle" vs. always improving "calculation of the tail factor")*
- *(b) whether or not it is generic or specific for the particular data type ("summation of any two triangles" vs. "annualization of the inflation rate" applicable only to inflation vector)*
- *(c) whether or not it is user interruptible (automatic "extraction of the last diagonal" vs. "loss development method", which requires user selecrion)*

In short, if an algorithm is a standard simple transformation of an object, it is most probably a method of the data class, and conversely, if an algorithm constitutes an actuarial method, it most probably belongs to the functional class.

Example 2. It makes a lot of sense to inherit Triangle, Vector and Diagonal actuarial classes from the Matrix class. Matrix implementation in existing spreadsheets or ActiveX components is extremely rich with properties). The OO designer just has to implement a few methods to create an algebra for triangles: the base transformations which would reduce operations on triangles to well-defined operations on matrices (inheritance at its best):

- *DiagonalsToColumns*
- *DiagonalsToRows*
- *RowsToDiagonals*
- *ColumnsToDiagonals*
- *DiagonalToVector(DiagonalNumber)*
- *VectorToDiagonal(DiagonalNumber)*
- *LastDiagonal*

For example, applying calendar year inflation to the triangle can be performed as a triad:

```
Triangle.DiagonalsToRows <-
Matrix.MultiplyByVector(InflationVector) <-
Triangle.RowsToDiags.
```

in more conventional notation:

```
Triangle.DiagonalsToRows.MultiplyByVector(InflationVector)
.RowsToDiagonals
```

Or, even less intimidating, taking the average of the last 3 *diagonals* can be reduced to the average of the last 3 *rows* in the matrix if `Triangle.DiagonalsToRows` is implemented (see Figure 7.)

Note that because Triangle inherits from the Matrix, it can use operations available to Matrix, in particular, multiplication by vectors and taking the average of its rows. Most of actuarial algorithms can be expressed through a very limited set of basic triangle and matrix operations; for the rest of algorithms users always have access to matrix elements.

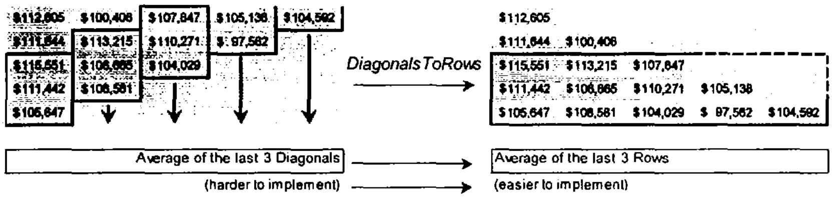


Figure 7

Example 3. A simple Chain-Ladder method rewritten in an OO fashion.

- *Step1 = InputTriangle.Accumulate(fromFirst, byAddition);*
- *Step2= Step1.Shift(toLeft, by:= 1)/Step1;*
- *Step3= Step2.DiagonalsToRows.RowsAverage(SelectedAverage);*
- *Step4= UserSelectedVector(Step3);*
- *Step5= Step4.Accumulate(fromLast, byMultiplication);*
- *Step6= Step1.LastDiagonal(asColumn) * Step5.Invert;*

Or even shorter (assuming the Input Triangle is cumulative):

*EstimateOfUltimate = InputTriangle.LastDiagonal(asColumn) * UserSelectedFactors(default:= InputTriangle.AgeToAgeFactors.Average(Medial, 5))*

A complete actuarial system has to extend its classification to include objects used by all types of actuarial activities: reserving, pricing and finances. Policy objects – highly structurized entities which store several dates along with the list of coverages and vectors of limits and attachment points – can be arranged in a hierarchy of their own (in such a hierarchy, finite reinsurance policy class can be derived from quote-share treaty class by adding aggregate limits property.) Vectors of inflation rates, sets of statistical distribution parameters and a simulation engine – these are the primary examples of actuarial objects to be included in the system.

An important implementation consideration is the links to the actuarial Data Mart or equivalent source of actuarial data. The structure of that data depository may impose restrictions (and requirements) on the availability of some desired categories and members in a hierarchy, and, therefore, the structure of the existing Data Mart should be a very important consideration in OO Analysis. It would be wise to build into the system an ability to anticipate future changes in the structure of available actuarial data and adapt its hierarchical organization to it, in other words, to build support for dynamic (data driven) hierarchy.

Currently pure OO databases and languages are not as ubiquitous as their relational and functional counterparts: Oracle, SQL Server and Sybase (the most ubiquitous databases) do not support inheritance and to call Visual Basic (one of the most ubiquitous programming environments) Object-Oriented is a very big stretch. Nevertheless, these impure OO environments support enough OO features for building applications and systems based on the main OO principles. In instances, when particular OO feature is not natively supported, it usually can be effectively emulated, so users and designers can reap all the benefits of OO applications today. In fact, a pure OO implementation of the actuarial system is less important than thorough and systematic OO Analysis of the actuarial workflow; that is, rethinking the whole actuarial process in terms of objects, methods, hierarchies and classifications.

Note how important the selection of a proper hierarchy is: we started discussing actuarial data chunks' categories and suddenly all the industry buzzwords like "Data Mart," "Object-Oriented Analysis and Design," "client-server architecture" and "data-driven technologies" came into play.

With the advent of OO databases, which store objects and thus have to store data along with operations, there are even more places for execution of the programming code. Indeed, where to implement object's functionality: on the server or on the client, inside the database or outside? Standard transformation routines, which are not subject to frequent modifications and user interruption, that is, abstract data types methods, are better placed on the server. Indeed, why request a triangle and then accumulate it on the client – let the powerful server accumulate it and transfer the result; or why request the whole triangle when only last diagonal is needed – let the server extract it before transferring the result. As for functional classes (actuarial methods) they also may take advantage of the server through request brokers like CORBA or DCOM. So, the system designer can build a distributed multi-user application using these tested and optimized actuarial procedures (implemented as methods of the functional classes) as construction blocks.

The author does not believe in a single monolithic application simultaneously suitable for pricing, reserving and financial analysis - he rather prefers a suite of applications each highly optimized for particular purpose, but founded on a base of comprehensive yet coherent set of common components (classes). Proper design and classification of actuarial objects, both abstract data types and functional classes, will enable actuaries to build such applications themselves.

Conclusion

Inheritance, a necessary requirement for any Object-Oriented system, naturally generates an internal hierarchy of the actuarial objects, while the database's requirement for identity of every object imposes an external hierarchy on the actuarial objects. This duality of the hierarchy reflects the fact that some categories in classification are used to determine which actuarial algorithm to use and represent differences in an object's internal structure and behavior, while other categories exist only to distinguish similar objects and define groups for aggregations. In other words, the external hierarchy is just a factorization of all actuarial objects by internal hierarchy. A deep understanding of these two distinct sources of hierarchies helps to optimize categorization of actuarial objects for their intended use – actuarial analysis, and also provides a basis for more effective and robust Object-Oriented actuarial applications.

Acknowledgements

The author would like to thank all the members of his immediate ("internal") and extended ("external") family for their understanding and support during the long hours dedicated to the work on this paper and taken away from them.

Stamford, 1998

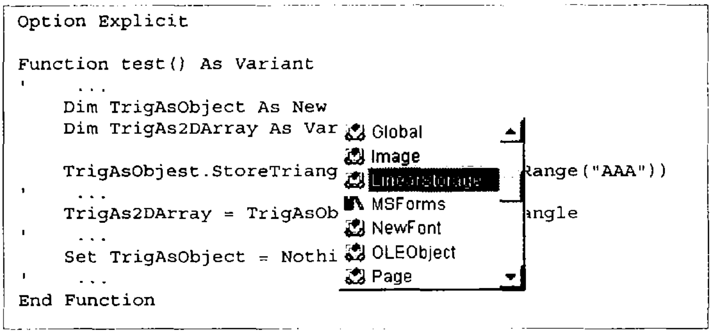
Appendix

Code samples are for illustration purposes only.

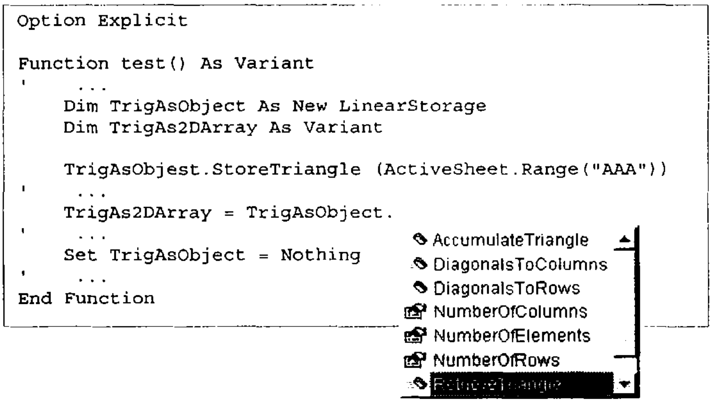
Example 1. The following text is a fragment of "LinearStorage" class implementation. Placed in

```
<class LinearStorage>

Private DynaStore() As Variant
Private nRows As Integer
Private nCols As Integer
Private nSize As Integer

Public Sub StoreTriangle(ByRef InputTrig As Variant)
    Dim i As Integer
    Dim j As Integer
    Dim k As Integer

    nRows = UBound(InputTrig, 1) - LBound(InputTrig, 1) + 1
    nCols = UBound(InputTrig, 2) - LBound(InputTrig, 2) + 1
    nSize = (1 + nCols - 2) * (1 + nCols - 1) / 2 + nRows

    ReDim DynaStore(1 To nSize)

    For j = 1 To nCols
        For i = 1 To nCols - j + 1
            k = (i + j - 2) * (i + j - 1) / 2 + i
            DynaStore(k) = InputTrig(i, j)
        Next i
    Next j
End Sub

Public Function RetrieveTriangle() As Variant
    Dim i As Integer
    Dim j As Integer
    Dim k As Integer
    Dim Output() As String

    ReDim Output(1 To nRows, 1 To nCols)

    For j = 1 To nCols
        For i = 1 To nCols - j + 1
            k = (i + j - 2) * (i + j - 1) / 2 + i
            Output(i, j) = DynaStore(k)
        Next i
    Next j

    ShowTriangle = Output

End Function
```

the VBA class module, this code will define an abstract data type called LinearStorage that will immediately become available along with VBA built-in data types.



It's *public* functions ("methods") and subroutines ("properties") will be available to all instances of this class.



Encapsulation. Note, that LinearStorage class includes both data (*nRows, nCols, nSize, etc..)* and operations (*StoreTriangle, RetrieveTriangle, etc..)*. External programs will not have direct access to any variables we store in the class as well as to any operations we designate as *Private*: When the designer wants external programs to access some data (e.g., *nRows*) he will implement a dedicated operation (e.g., *NumberOfRows*), where class will have a chance to validate input and perform necessary transformations of related items (e.g., *nSize.*)

Glossary

A list of the most popular and influential variants of definitions for the most important OO concepts (mostly from [6] and [10]). Items are listed in the order of appearance in this article.

object *n.* 5.(a) any instance of one or more classes or types... 2.(b) any encapsulation of properties (e.g., data) and behavior (e.g., operations)... 1.(c) any real or abstract thing about which we store data and the operations to manipulate those data... 2.(a) any identifiable, encapsulated entity that provides one or more services that can be requested by a client... 1.(a) any abstraction that models a *single* thing... 9. any person, place or thing...

Synonym: INSTANCE

class *n.* 5. any set of objects that share the same or similar features... 4.(b) any implementation of a type of objects, all of the same kind... 2. any possibly generic factory of instantiation of instances... 7. the unit of modulation, data hiding, and encapsulation... 1.(b) any concept that has members... 1.(a) any uniquely-identified abstraction (i.e., model) of a *set* of logically-related instances that share the same or similar characteristics...

Synonym: TYPE

encapsulation *n.* 1.(b) the packaging of operations and data together into an object type such that the data are only accessible through messages to the object... 1.(a) the physical localization of features (e.g., properties, behaviors) into a single black-box abstraction that hides their implementation behind a public interface...

Synonym: INFORMATION (DATA) HIDING

inheritance *n.* 1.(b) the construction of a definition by incremental modification of other definitions... 3.(b) a mechanism that permits classes to share characteristics...

polymorphism *n.* 2. the ability of a single name to refer to different objects (i.e., objects of different classes)... 1.the ability of a single name to refer to different things having different forms...

hierarchy *n.* 1. any ranking or ordering of abstractions into a tree-like structure...

object identifier (OID) *n.* 1. the simple identifier permanently assigned to each object that is a) unique within some scope (i.g., an application), b) independent of the object's properties and state, c) constant during the existence of the object...

identity *n.* 1. the use of identifiers rather than keys[♣] to uniquely identify objects...

[♣] keys (fields) is a notion from the Relational Database vocabulary

persistence *n.* 1. the ability of an object to continue to exist after the execution of the program, process, or thread that created it...

object-oriented programming *n.* 1. any application specific programming resulting in programs that consist of collection of collaborating objects, which have a unique identity, encapsulate properties and operations, communicate via message passing, and are instances of classes related by inheritance, polymorphism and dynamic (run-time) binding...

dimension *n.* 2. an index for identifying values within a multi-dimensional array... 1. A *dimension is a structural attribute of a multi-dimensional array that is a list of members,* all of which are of a similar type in the user's perception of the data.

Example: months, quarters, years, etc., make up a time dimension; cities, regions, countries, etc., make up a geography dimension.

dimension member *n.* 1. a discrete name or identifier used to identify a data item's position and description within a dimension...

member combination *n.* 1. an exact description of a unique cell in a multi-dimensional array, consisting of a specific member selection in each dimension of the array...

generation *n.* 2. in a hierarchy, the distance from the top... 1. members of a hierarchy have the same generation if they have the same number of ancestors leading to the top...

Example: in a time dimension years are generation 1, quarters are generation 2, etc..

level *n.* 2. in a hierarchy, the distance from the bottom... 1. members of a dimension with hierarchies are at the same level if, within their hierarchy, they have the same maximum number of descendants in any single path below...

Example: in a time dimension months are level 0, quarters are level 1, etc..

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Watch Your TPA: A Practical Introduction to Actuarial Data Quality Management

Aleksey S. Popelyukhin, Ph.D.

Watch your TPA:

A Practical Introduction to Actuarial Data Quality Management

Aleksey S. Popelyukhin, Ph.D.

> *"Dear Cardmember, the 1997 Year End Summary of your account regretfully contained an error: we discovered that one or more of your transactions were "double counted" – please, accept our sincerest apologies for the error and for any inconvenience it may caused you."*
>
> ***Major credit card issuer***

Introduction

We live in the era of information: an enormous amount of information. Information gets collected, stored, processed, summarized and distributed; there are too many opportunities for errors to sneak in. Data is translated, transformed and aggregated so often, that it is inevitable that some results of the data processing are imprecise.

We may experience this data infidelity elsewhere every day. Once in a while, some bank counts every withdrawal twice, some airline issues two tickets for the same reserved seat and some healthcare provider goes broke due to errors in its financial reports. And we are yet to witness the consequences of the "Year 2000 bug".

The actuarial field can not escape the effects of data errors, either. For example, the NCCI has to restate published LDF's every year (compare [1], [2], [3]) due to errors/restatements in the summaries from information providers.

With the proliferation of the Data Warehousing projects, Data Quality issues come into the spotlight: inaccuracies in data become very apparent. The Data Warehouse, as a source of quality data for analysis and the decision-making process ([4]), requires data to be cleaned up before entering the system.

There is extensive literature on the topics of Data Quality Management ([5]), measurement of the value of information ([6]) and data stewardship ([7]), which is highly recommended for reading. However, sources of information on particular problems with **actuarial** data are scarce, and usually not readily available to actuaries ([8]-[10]). This paper, in an attempt to correct that situation:

- *discusses Data Quality concepts and data clean-up processes addressing specific issues of actuarial analysis requirements,*
- *highlights the inevitability of actuarial involvement in data management procedures,*
- *provides practical examples of the Data Quality Shield's filters and routines derived from the study of the data samples from 43 TPA's and*

- *emphasizes that the quest for actuarial data quality does not stop once data are downloaded in the company-wide Data Warehouse or departmental Data Mart.*

Data Quality Shield

According to Andrew Ippilito (see [11]), data has a number of quality characteristics:

- *Accuracy: the measure of the degree of agreement between a data value and a source assumed to be correct.*
- *Completeness: the degree to which values are present in the attributes that require them.*
- *Consistency: the requirement that data be free from variation or contradiction and satisfy a set of constraints.*
- *Timeliness: the extent to which a data item or multiple items are provided at the time required or specified (a degree to which specified values are up to date)*
- *Uniqueness: the need for precise identification of a data record (and data key values).*
- *Validity: the property of maintained data to satisfy the acceptance requirements of classification criteria and the ability of the data values to pass tests for acceptability, producing desired results.*

Data sets which do not satisfy all the quality characteristics constitute a data quality problem. Often a data quality problem requires two separate efforts: a project to correct existing data and a project to correct the cause behind the data problem. In a typical situation, all data sources are accessible, (for example, mainframe legacy systems within one company) and once the faulty source is identified, the fix is feasible.

Unfortunately, the typical insurance/reinsurance company relies on multiple **external** sources for actuarial data. Third Party Claim Administrators (TPA) monthly summary reports (Loss Runs) are a primary examples of such sources (other examples are industry statistics from NCCI, ISO or RAA bulletins). For the purposes of this article, the company's own legacy systems can be considered as one more (self) TPA, as it is usually external to the actuarial departmental Data Mart and is (potentially) subject to the same types of errors.

There is a limited number of available options for eliminating the cause of data problems in an external data source:

- *External: certification of the TPA information systems.*
- *Internal: deployment of a Data Quality Shield.*

A **Data Quality Shield** is an integrated set of standardized routines optimized for every external data source and comprised from pre-load data filters and translators, along with post-load data analysis tools, statistical diagnostics and quality alarms. This type of integration is needed in order to address two specific distinctions of the actuarial data: multiple *external* sources of data (TPA's) and the *time-variant* nature of intended applications (actuarial methods).

The purpose of a Data Quality Shield is to:

- *Establish standards, (discovering and enforcing business rules, including time-variant business rules)*
- *Validate Input (checking that data values satisfy data definitions)*
- *Eliminate redundant data*
- *Resolve data conflicts (determining which piece of redundant, but not matching data is the correct one)*
- *Propagate corrections and adjustments to prior evaluation for the time-variant data*

The Data Quality Shield's goal is to discover business rules for the actuarial data which may serve as a foundation for the testing and certification of TPA systems.

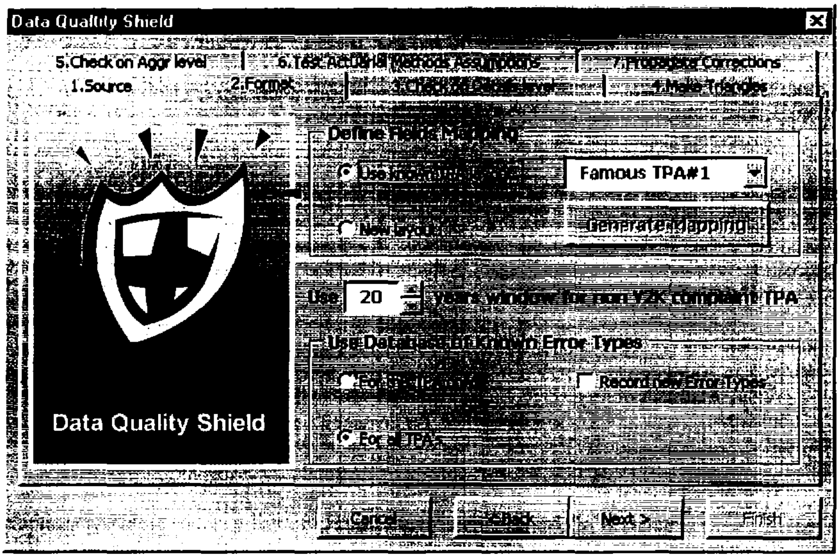

Figure1

In order to create a data quality shield for the actuarial Data Mart in his own company, the author analyzed Loss Runs from more than 40 TPA's and concluded that (currently) no TPA provides data which completely satisfies the Data Quality definition. As a result of his research, the author created a list of typical errors and potential problems and devised a set of routines to identify and fix them.

Typical Problems

As real life experience shows, nothing, not even the most evident data quality requirements, can be taken for granted – even the most obvious actuarial business rule has to be tested and enforced. Every single type of error or deficiency listed below has been detected in at least two TPA Loss Runs.

1. Fields availability

Quality data by definition has to satisfy the completeness and uniqueness requirement: enough fields have to be provided for the possibility to

> *check policy conditions.* For example, the Location field is required if deductible differs by state,
>
> *perform actuarial analysis.* For example, the Report Date field is required if the coverage is "claims-made",
>
> *uniquely identify each record.* For example, the Type of Coverage field is required if the same accident is covered by Worker's Compensation and Employer's Liability.

Of course, fields designated as required can not contain NULL values, that is, be empty for any particular record.

2. Duplicates ("double counting")

- *Source of the problem*

  There are several types of redundant records created with different causes:

  > *True duplicates (same ClaimID).* Possible cause – inaccurate join of the tables with "many-to-many" relationship (for example, the Payments and Recoveries tables with multiple records per claim in both of them joined prior to aggregation).
  >
  > *Duplicate files (different ClaimID, but same Accident Date and ClaimantID).* Possible cause – poor checking against existing records on entry (the TPA system erroneously treats the same claim with a slight variation in claimant name or with a supplied middle initial, as a different claim with its own ClaimID).
  >
  > *Insufficient number of key fields.* Possible cause – missing Claim Suffix or Type of Coverage fields – a deficiency of the Loss Run rather than a whole TPA system problem.

- *Detection*

  > Duplicates can be detected by a simple aggregation (GROUP BY) query with the application of the post-aggregation filtering (HAVING):

```
SELECT ClaimID
```

```
FROM LossRun
GROUP BY ClaimID
HAVING Count(ClaimID) > 1
```

To see all duplicate records rather than a single representative from each group, one can use an embedded query (a query within a query):

```
SELECT *
FROM LossRun
WHERE AccDate In
    (SELECT AccDate
    FROM LossRun
    GROUP BY AccDate, ClaimantID
    HAVING Count(*)>1 And ClaimantID =LossRun.ClaimantID)
ORDER BY Accdate, ClaimantID
```

Records with values matching in any number of fields can be found with the help of such embedded queries. For example, one can detect multiple claims from the same claimant reported on the same date (GROUP BY ReportDate, ClaimantID).

3. Unidentified Occurrences

Depending on the actuarial methodology used to count claims or reinsurance contract conditions, it is crucial to know which groups of claims constitute the same accident or occurrence.

- *Source of the problem*

  Some TPA's do not provide and frequently don't even maintain exact criteria (like Claim Suffix field) for determining occurences, others concatenate Claim Suffix into ClaimID.

- *Workaround*

  In the former case, one can use an embedded query, described above, grouping claims by Accident Date and Location to extract a list of claims, which potentially may constitute the same occurrence. Unfortunately, farther investigation with additional help from the TPA will be required.

  In the latter case, the use of built-in or user-defined string functions (e.g., *left()* and *length()*) in a GROUP BY clause of the query may help to break the ClaimID into an OccurrenceID and a Claim Suffix:

```
SELECT left(ClaimID, length(ClaimID)-3), count(ClaimID) AS Claimants...,
sum(Amount) AS TotalPerOccurence
FROM LossRun
GROUP BY left(ClaimID, length(ClaimID)-3)
ORDER BY left(ClaimID, length(ClaimID)-3)
```

4. Recoveries (SIF, salvage & subrogation).

Recoveries may be reported as a separate (from payments) table, may be reported late or may not be reported at all.

- *Source of the problem.*

  While loss payments are made through TPA system, recoveries usually are credited directly to the primary insurer. Thus, at least two sources of data have to be synchronized and related in order to generate net amounts correctly.

- *Workaround*

  To relate tables of payments and recoveries one can use left join (beware of SQL syntax variations in different RDBMSs) of pre-aggregated Loss and Recovery tables (joining non aggregated tables may lead to appearance of duplicates (see "2. Duplicates"):

```
SELECT p.ClaimID, ..., p.GrossLoss, r.Recovery
FROM LossRunPayments AS p, LossRunRecoveries AS r
WHERE p.ClaimID = r.ClaimID (+)
```

5. Consistency of the redundant fields

Some fields are interdependent, and when information in these fields is inconsistent, it is unclear which field to trust. Examples of dependent fields are too numerous to list here, but a few of the most common are:

closed and reopened claims have "last closing" date

open claims have non-zero reserves, closed claims have zero reserves

incurred amount equals paid amount plus outstanding reserve

total paid amount equals sum of indemnity, medical and expense payments (for Worker's Compensation line)

- *Source of the problem*

  Apparently some TPA systems do not have triggers on the closing claim event. Such a trigger is supposed to nullify reserves and insert closing date every time claim is closed.

  As for arithmetic inconsistencies, there are two possibilities: if the TPA system stores redundant amount fields, then system does not react adequately on the changes (adjustments) in the values in the fields; if TPA system stores only independent fields, then it is Report Generator that is broken.

- *Detection and Workaround*

Given "write" access to the data repository and information on which fields are correct, one can execute UPDATE SQL query to restore consistency:

```
UPDATE LossRun
SET Incurred = Paid + OSReserves
WHERE NOT(Incurred = Paid + OSReserves)
```

6. *Dummy records*

There are several types of redundant records, which do not belong in the LossRun in the first place. These records are filtered out by the TPA's internal tools, and thus remain practically invisible for insiders. However, with the proliferation of online access and digital exchange, these dummy records can be potentially accessed by outsiders, and there is nobody to warn the external user that, for example, record type "99" is a subtotal and has to be filtered out to avoid double counting.

- *Source of the problem*

  Subtotals. This is "no-no" of the database design – subtotals should not be stored in the same table as original data: that is what Data Marts with their pre-summarized tables are for.

  Dummy claims for "hard to allocate" ALAE. Similar to subtotals, this problem has two causes: one is the inflexibility of TPA system to accommodate all types of allocated payments; a second is the mismatch in the periodicity of summaries of such payments (for example, only quarterly reports from the outer source are available to the TPA)

  Test claims – remains of database development projects. This is a development culture problem: systems have to be cleaned up before deployment.

7. *Year 2000 compliance*

Still a significant issue for many TPA's: 9 out of 43 still allocate just 2 digits for the year value either in their own systems or in the Loss Runs they generate. Another related problem is the handling of NULLs in date fields, for example, in the "Closed Date" field for open claims one can find anything from 01/01/01 to 0 to 11/01/1901 to 1/0/1900 (Excel's representation of 0 as a date).

8. *Disappearing claims*

Many actuarial methods assume – and not without reason – that the number of claims never decreases in time, or more precisely: a claim once reported will appear on all following Loss Runs. In reality, this assumption does not always hold true.

- *Source of the problem*

  Due to inevitable miscodings, some claims end up in the wrong Loss Run. Once identified as "voided", claims have to be removed from all past Loss Runs (see "13. Propagation of corrections") – that does not always happen.

- *Detection*

  A simple SQL query may help identify claims that "disappeared":

```
SELECT *
FROM LossRun
WHERE Evaluation = PreviousEvaluation
AND ClaimID Not In
    (SELECT ClaimID
    FROM LossRun
    WHERE Evaluation = CurrentEvaluation)
```

9. Non-monotonic losses

Another popular actuarial assumption is that cumulative direct (gross of reinsurance and recoveries) payments are non-decreasing in time.

- *Source of the problem*

  Some drafts that TPA's pay to claimants are voided for some reasons.

- *Detection*

  The so-called self-join SQL query helps to isolate unusual reductions in payments:

```
SELECT LossRun.*
FROM LossRun, LossRun As PrevLossRun
WHERE LossRun.ClaimID = PrevLossRun.ClaimID AND
LossRun.Evaluation = CurrentEvaluation AND PrevLossRun.Evaluation =
PreviousEvaluation AND LossRun.DirectPTD < PrevLossRun.DirectPTD
```

10. Consistent fields definitions

Before validating any business rules and running any tests on TPA data, one has to make sure that fields satisfy standard definitions (i.e., for Statutory Page 14 Data or the ISO statistical plan). Once consistency of field definitions is established, various constraints and validation rules can be tested. For example, one would expect losses to be positive; recoveries to be negative; accident date not to exceed report date, not to exceed closing date, not to exceed evaluation date, etc.

11. Online access and digital exchange

The proliferation of online access to TPA data has created one more type of problem – download integrity. The online session may result in the download of an incomplete set of data or, alternatively, undesirable auxiliary records (see "6. Dummy records"). One of the digital exchange formats, for example, specifies three records of different types for every claim. Thus, every download has to be tested for claim records integrity (every claim has all three records) as well as for completeness of the download (comparison to control subtotals info).

12. Data Entry human errors

An inevitable source of errors cured only by the accuracy of company employees and the system of database self-testing and data entry validation routines.

13. Propagation of corrections

Due to the time-variant nature of Data Warehouses and Data Marts, it is not enough to maintain data consistency in every given time slice – consistency through time is as important. It is crucial, that any adjustment due to miscoding or other error (see "8. Disappearing claims" and "9. Non-monotonic losses") be propagated back to previous evaluations.

Summary

Data sets with even single typical error fail to satisfy data quality definition cited above. Indeed, Loss Runs with error types 6, 8, 9, 10, 12 fail on the requirement for *accuracy*; 1, 2, 3, 7, 8, 11 – for *completeness*; 5, 13 – for *consistency*; 4 – for *timeliness*; 1, 2 – for *uniqueness*; 1, 2, 3, 6, 7, 9 – for *validity*. Unfortunately, in addition to typical problems some sources have their unique (but, nevertheless, malicious) errors.

Legacy systems

All the examples above contains snippets of code written in SQL – a Structured Query Language invented by IBM in order to standardize requests to the database management systems (DBMSs). While every modern DBMS supports SQL, mainframe-based legacy systems usually don't. Absence of SQL support, however, should not be a reason for allowing data errors to slip through.

As long as the reader understands that SQL is just a parsable set of instructions allowing the optimizer to perform a sequence of sorts, scans and lookups, it becomes clear that the same functionality can be achieved using Quick Sort combined with subroutines in PL/1, Cobol or SAS. For example, in order to find and display duplicate records, one would perform a sort placing potential duplicates one after another, and then scan record by record, comparing the previous record with the current one (if records don't match, the user would reset counter of duplicates to 0, otherwise incrementing it by 1; if resulting value of the counter equals 1, the previous record would be placed in the output set; in addition, a positive value of the counter would trigger output of the current record).

In fact, any traditional programming language, being computationally complete, is more capable than SQL. It is just that as an established standard, with it's ease of learning and use, database optimization, and wide availability, SQL has become such a popular language. As the examples above demonstrate, SQL is simple enough for an actuary to run quite a sophisticated query against Data Mart or Loss Run data, yet it so powerful and useful - it definitely deserves to be included in the actuarial syllabus (sometime in the future).

Quality Requirements for Certification process

The existing situation for TPA data quality is unacceptable. In contrast with the explicitly spelled out list of "Year 2000 (Y2K) compliance" requirements, there is no commonly accepted list of "TPA data quality" criteria. And while companies expend a great effort to ensure that all their data sources do satisfy these rigid Y2K requirements, the author is not aware of any significant centralized effort directed to the clean-up of data supplied by TPA's. Similar to the Y2K situation, TPA's have to provide clean data, but they (currently) don't.

It is possible, with the help of actuaries and data administrators, to compile a list of standard tests for the TPA system to satisfy in order to be certified as "actuarially compliant". The typical problems list above may serve as a starting point for such a compilation.

Data that ultimately end up in the actuarial Data Mart move through the following stages, all of which can serve as a source of errors:

- *collection,*
- *storage,*
- *report generation,*
- *communication/distribution.*

For a TPA system to be called "ideal", it has to pass error tests at every stage. Other requirements to the ideal TPA system would include:

- *Flexibility to accept changes: endorsements, adjustments.*
- *Availability of history (previous evaluations).*

As the only stage that involves both the TPA and data recipient, the communication (digital exchange) stage has to be examined most carefully. Any digital interchange standard along with the format should include a list of checks and balances. Introduction of the standard for information exchange without built-in safeguards and a list of testable quality criteria, while possibly eliminating one type of error (e.g., human errors on data re-entry), will inevitably lead to proliferation of other types of error (e.g., duplicates).

An argument for the companies – consumers of TPA data – to be involved in the fixing of TPA problems, even if errors are in their favor, is that errors in their favor are still errors. They are indicators of poor data quality and it's just a matter of time when inevitably they will affect these companies negatively.

Actuaries to the Rescue

While one can rely on the FDA for food quality certification, one should not completely disregard one's own immune system. The same rule of thumb applies to actuarial data quality. No matter how clean and consistent TPA data will become, or whether certification for TPA computer systems will be introduced, it is the data consumer's responsibility to run the last error check and, thus, actuaries will always remain the company's last line of defense against errors.

The list of the typical errors found in TPA's Loss Runs can be sharply divided into two major categories:

- *Violations of static business rules (those which need single Loss Run present to be identified and fixed) and*
- *Violations of time-variant business rules (those which track changes in time and need multiple Loss Runs for identification).*

Static, that is, time-invariant business rules, can be expressed in the Data Mart's metadata format and enforced by validation processes, while "dynamic", or more precisely, time-variant rules, can not. Also, "dynamic" errors require significantly different procedures for discovery vs. correction. While the correction of static data problems has to be and can be addressed by the TPA's, "dynamic" data problems belong to consumer of the information domain, because the level of sophistication, actuarial expertise and customization required for "dynamic" problems resolution is usually beyond TPA's core business – administration of claims.

Given that

> Data Marts provide ***time-variant*** data depository,
>
> TPA's provide data which violate ***time-variant*** business rules,
>
> people who study ***time-variant*** regularities in the insurance companies and, thus, require high quality ***time-variant*** data are called actuaries,

it is clear that they are the best suited professionals to discover *time-variant* business rules and develop routines for protection against *time-variant* errors.

The Data Mart created from TPA data can serve not only as a source of decision-support information, but also as a source of alarms about actuarial quality of the data. The time-variant property of a Data Mart makes it the ideal platform for identifying "dynamic" errors, and actuaries are the most qualified people for designing data quality shields against this type of errors. Once found on the aggregate level, adjustments to the data have to be propagated back in time and granularity. Business rules discovery is an iterative process, with the Data Mart improving after each iteration.

Testing Assumptions of the Actuarial Algorithms

Data quality issues can not be considered separately from the application of the data. Data accumulated in the actuarial Data Mart are supposed to be used in the pricing and reserving algorithms.

Any algorithm – an ordered sequence of operations – has assumptions (explicit or implicit) to be satisfied in order for the result to be correct and reliable. Thus, before starting any calculations, the algorithm's assumptions have to be tested. A good example would be checking whether a given number is non-negative prior to any attempt to extract a square root from it.

Despite the evident importance of the assumption testing and availability of testing routines (see, for example, [12] - [13]), an unacceptably large number of actuaries don't test assumptions. The use of results taken from calculations on untested data will inevitably lead to wrong decisions and misleading conclusions. While the determination of implicit assumptions of actuarial algorithms is an extremely fascinating topic by itself, deserving separate research, this paper is concerned with the data quality aspect of assumption testing.

It turns out that assumption testing is one of the main sources of time-variant business rules. Indeed, a monotonically increasing number of claims is both a time-variant rule and a requirement for the applicability of the Berquest-Sherman algorithm; the same for the assumption of lognormality in ICRFS [14] which coincides with the time-variant rule that requires incremental gross payments to be positive. The failure of the portion of data to satisfy an assumption test can be sometimes caused by data error and lead to discovery of the time-variant business rules, which were violated.

Precise measurement of the impact that data errors have on actuarial algorithm outcomes is beyond the scope of this paper. However, common sense and rough estimates suggest that erroneous claim counts may significantly distort Fisher-Lange method results and large loss frequencies used for pricing; incorrect amounts of losses may affect Chain-Ladder estimates of ultimates; and misreported recoveries may bend loss development patterns, which may result in many negative consequences. Errors in the data may render some of the more advanced actuarial methods inapplicable, potentially leaving actuaries without the best possible estimates. And in a cumulative world of Data Marts, errors do not disappear – they have an undesirable tendency to propagate forward: data points in every evaluation accumulate errors from the previous ones.

Thus, pre-analysis diagnostics of actuarial data, whose purpose essentially is assumption testing, can be viewed as a part of the data quality process and time-variant business rules enforcement, once again highlighting the importance and necessity of the actuarial involvement in it.

Outliers

Another area of actuarial attention should be determination and investigation of the sources of outliers.

Outliers are observations too distant from the expected values. Proper treatment of outliers is important, because the usual regression parameters are significantly affected by them. There are two major ways to treat outliers: robust algorithms and elimination (zero-weight approach).

Robust algorithms help not only avoid distortion of the output, but also determine outliers, which reflect unusual behavior and for which further investigation is necessary.

However, the origin of some outliers is just data error, and these outliers are usually thrown away. Detection, determination and prevention of that type of outliers consequently become an important data quality issue, because instead of throwing away outliers, clean data could provide one more useful observation.

Conclusion

In the world of imperfect external data sources and nontrivial time-variant business rules, the data quality shield's dual approach (pre-load filtering and post-load statistical analysis) is the only practical solution to actuarial data quality problems. Deployment of the data quality shield may significantly improve company's bottom line both directly and indirectly. Potential savings on overpayments to TPA's measured in millions of dollars with significant reduction in company's losses (and consequently, reserves) is not a bad payoff for the design and regular execution of several database queries and custom programs. A fresh review of performance in some business segments supported by correct data may lead to reevaluation of their profitability and may affect important business decisions (the author witnessed exactly that in his own company).

The author views the actuarial process as an inseparable trinity of input, analysis and report phases (see [15]). With this paper, the author tries to demonstrate that for high quality reports based on high quality analysis, actuaries need high quality data; and that nobody is better suited for the determination and enforcement of data quality tests and time-variant business rules than actuaries. Therefore, the author maintains that actuarial involvement in the data management process and data ownership and stewardship is not even a question – it is a tautology.

Clean external data provide a healthy start for the whole actuarial process. To ensure external data quality some type of governing body could to be established. Equipped with a battery of standard quality tests (both static and time-variant) provided by the actuaries, this organization could certify TPA computer systems for use in actuarial applications.

With or without system certification process in place, the situation is steadily improving:

- *Many TPA's, in order to prepare for Year 2000, are updating their systems addressing data quality problems as well.*
- *A proposed electronic data exchange standard (EDI) is now being implemented, requiring TPA's to maintain enough detail for actuarial analysis and accounting calculations.*
- *The move from mainframes to client-server solutions is providing an opportunity for significantly better data quality control.*

Still many problems with TPA data remain. The author hopes that this article will trigger papers from his colleagues from ISO, IDMA and NCCI, where they will share their thoughts on the topic.

Technology today allows more involved actuarial participation in the assurance of the data quality. Modern database management systems, Data Marts and Data Warehouses allow actuaries to access more detail in their data with the most powerful query and analysis tools ever. The author hopes that as a result of reading this paper, some actuaries will establish a standard set of queries, routines and alarms for data quality assurance procedures and will begin a constantly improving data monitoring and correction process.

Epilogue

As for the letter quoted as an epigraph, the author (with the help of his personal data quality shield) discovered duplicates himself, called the bank and triggered corrective action, which benefited everybody.

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Stamford, 1998

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Using Neural Networks to Predict Claim Duration in the Presence of Right Censoring and Covariates

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HNC Insurance Solutions is a business unit of HNC Software Inc. and was formed in the 1998 merger of CompReview Inc. and Risk Data Corporation. HNC Insurance Solutions is an insurance information service and statistical research company which creates and markets solutions for the insurance industry.

Abstract

We present a general methodology for fitting feed-forward neural networks when both right censoring and covariate information (claim attributes) exist. Right censoring occurs when only intermediate, but not final values of a time-dependent variable (such as claim duration) are known for some data points, and final values of the variable are known for all other observations. This situation frequently arises in casualty insurance when there are active claims in an analysis data set. The techniques we develop are applicable for estimating the distribution of claim lifetimes when awards are disbursed over the unknown claim life. The neural-network framework allows us to handle complex relationships between the claim attributes and claim duration.

We will derive a generalization for right-censored data of the back-propagation method used for fitting feed-forward neural networks. A connection between least squares estimation and maximum likelihood estimation will be used to establish the generalization. A typical cross-validation approach to modeling will be described to reduce over-fitting. An application of our methods is demonstrated for predicting the duration of a claim in worker's compensation insurance in the presence of covariates.

1 Introduction

In casualty insurance, it is common for the payments on a claim to be disbursed over time. For example, in workers' compensation insurance, a claim is filed some time after injury to the worker and payments are made on the claim over a period of several years. In this setting, most data samples contain claims that are still active and do not have complete information. Therefore, when building models to estimate claim duration, we need to use techniques designed to handle incomplete observations.

When a claim is open at the time of sampling, the claim duration is said to be right censored. The claim is right censored because all we know is the final claim duration exceeds the current duration. From a graphical perspective, the right end of the claim's timeline has been hidden from view. For example, if the claim is open for 16 months prior to sampling, we know that at closing the claim's duration will exceed 16 months.

When estimating the duration of a claim, it is important to consider the point in the claim's life at which we are making the estimate. For example, if we make a prediction on the day that a claim is reported, we will be limited to available information. Alternately, if our prediction is made after three months of claim activity, we will have more information. Models should reflect the point in time at which data are available. For example, we may want to use the total medical paid at six months as a predictor of duration. However, this information will not be known at the beginning of a claim's life. Therefore, this model is applicable only for predictions at 6 months duration for claims that exceed 6 months duration.

Estimating claim duration and the distribution of durations can be useful for a number of reasons. For example, there may be a need to make an early assessment of the claim's severity based on all available claim information. This type of procedure may be useful in providing an index of the claim's severity relative to claim duration. Methods such as these provide a systematic way of evaluating a large amount of claim information in an efficient and logical manner. Using a neural network to predicts duration provides a comprehensive method that uses complete historical data to develop the predictions of duration.

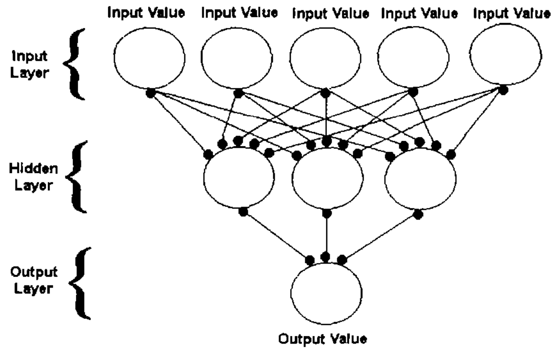
In this paper, we develop methods to model the relationship between claim characteristics and the duration of a claim. These methods use a generalization of the back-propagation algorithm to right-censored data for feed-forward neural networks. Back-propagation is a numerical optimization technique that is commonly used to estimate a neural network's parameters (often referred to as weights in the neural network literature). Feed-forward refers to the specific order in which each subject's information is processed. The techniques developed here build on ideas presented in (Faraggi & Simon 1995, Liestol, Andersen & Andersen 1994). We will generalize the neural network, back-propagation algorithm to right-censored data using a likelihood-based approach.

1.1 Introduction to Neural Networks

Neural network models are closely related in form to many commonly used statistical techniques. (Wasserman 1989) provides a technical introduction to neural networks. (Sarle 1994) describes connections between several statistical procedures and neural networks. Among the procedures he discusses are linear regression, logistic regression, discriminant analysis, multivariate linear regression, and principal component analysis. Most of these techniques are shown to be special cases of neural networks. The flexibility of neural networks to apply to a wide variety of modeling situations makes them valuable as a general framework for statistical analysis. This paper will draw one more connection between neural networks and statistical procedures. We will show how the neural network framework can be used to model continuous outcome data with right censoring.

Figure 1 is a graphic representation of a typical neural network architecture. Such a diagram is commonly used in literature on neural networks. In the figure, the flow of information, or data processing sequence, is downward. Because the flow is only one-way and begins with the input variables, the network is said to be a feed-forward network. Each circle in the figure is called a node, or "processing unit." In actuality, each node represents the evaluation of a function. Estimation of the functional parameters is called "fitting." Thus, each node can be thought of as a separate regression. Also, each row of circles in Figure 1

Figure 1: Diagram of a Feed-Forward Neural Network



is referred to as a "layer."

Consider the nonlinear regression

$$y = 4\cos(7 + 3x).$$

For a given value of x, the function $7 + 3x$ is first evaluated and then the cosine of the intermediate value is calculated. In neural network problems, x corresponds to the input level, $7 + 3x$ refers to the input to the node in the hidden layer, and cos(.) is the activation function of the hidden layer's node, and the result of $\cos(7 + 3x)$ is the output of the hidden layer's node. The layer of nodes is said to be "hidden" because it is unavailable to the network's user. The output of the hidden layer is then multiplied by 4 and passed to the output layer. The information flow is said to be one-way because a given x value determines the value for $7 + 3x$ which in turn determines the output of the hidden layer and the output layer through the model weights. In this setup, there is only one hidden node and the model weights are 7, 3, and 4.

In the general representation of Figure 1, the top layer of nodes represents the input data or predictor variables, where each circle signifies one continuous variable, or one level of a categorical variable. The middle layer represents the hidden layer of the network. There are different projections of the input layer into each circle in the hidden layer. A projection is simply a linear combination of the input variables. The output from each node of the first hidden layer is typically scaled to the unit interval by an activation function. The final bottom layer represents a single linear combination of the hidden layer and is called the prediction or output layer. This diagram depicts a one hidden-layer model, but more hidden layers can be added.

A neural network can model complex relationships between the input and output variables. Such relationships include interactions between multiple input variables and nonlinear transformations of input variables. With more traditional analysis methods, discovering subtle interactions and transformations may be time-consuming and difficult, if not impossible. With a neural network, the network architecture is easily adapted to include subtle interactions and transformations.

Neural networks can be powerful tools for modeling claim duration and costs. To intuitively understand this assertion, assume that the mean of the output variable can be accurately approximated by a (possibly very complex) continuous function. Consider Figure 1 with only one hidden layer and assume the output of each hidden node is a simple continuous function. With linear combinations of the certain simple continuous functions, the result can be made arbitrarily complex by utilizing a sufficiently large number of hidden nodes. This allows the neural network to approximate a wide class of functions.

Parameters of a feed-forward neural network are often estimated using a technique known as the back-propagation algorithm. The algorithm is an optimization technique and is related to the gradient descent algorithm. Some details of the algorithm are presented in section 2.2. Interested readers are referred to (Wasserman 1989) for more details.

Example 1.1: Representing Nonlinear Deterministic Functions To demonstrate the ability of neural networks to capture nonlinear relationships, we generated data randomly from the polynomial equation

$$z = \frac{1}{3}x^3 - x + 1. \tag{1.1}$$

We generated values of x from a uniform distribution on the interval $[-3, 3]$ and determined z values using equation 1.1.

Figure 2 shows the fit to these data of a feed-forward neural network with one hidden layer and three nodes in the hidden layer. Methods for specifying the form, or architecture, of a neural network and for estimating its parameters will be described in the next section. This example is intended solely to demonstrate that neural networks can accurately approximate nonlinear relationships.

The solid line in Figure 2 represents the neural network equation and the superimposed scatter plot represents the true values that were generated. Figure 2 demonstrates the ability of the neural network to adapt to nonlinear relationships with relatively few nodes in the hidden layer. The general mean structure of the neural network allows us to represent a polynomial relationship without specifying quadratic or nonlinear terms in our model.

2 Neural Networks for Right-Censored Data

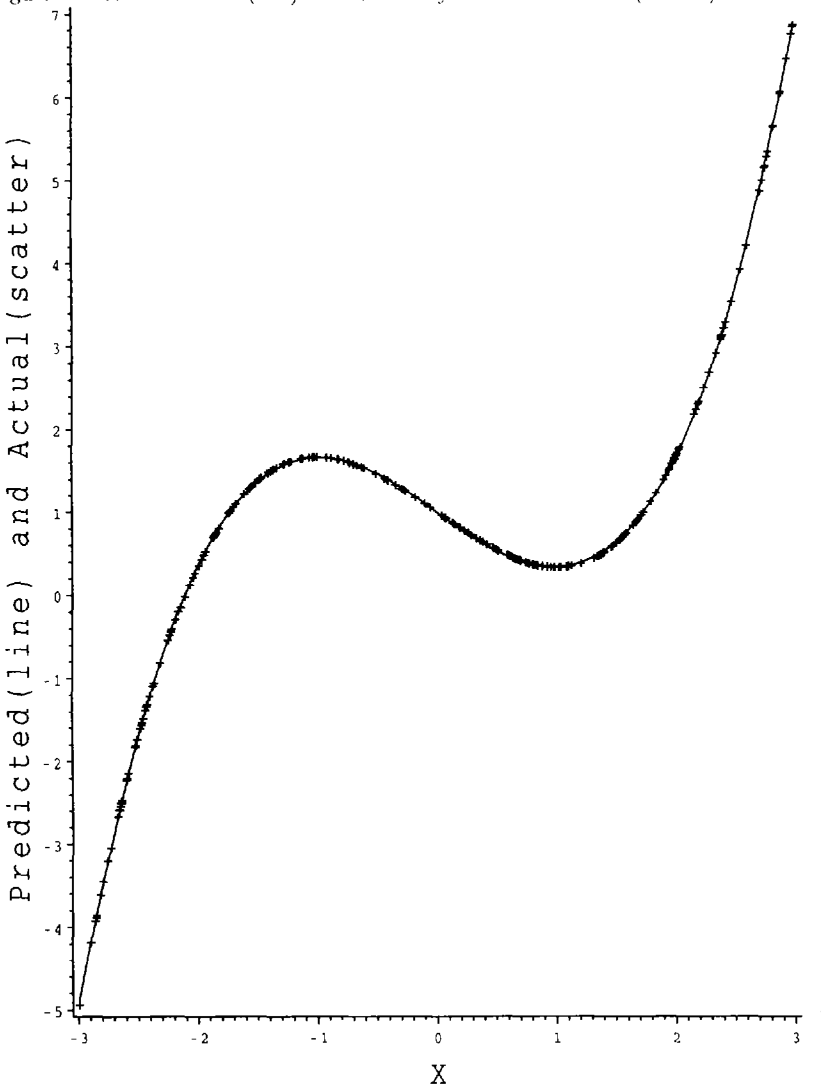
The feed-forward neural network is analogous to a regression model because there is a set of input values, typically called predictors in statistical models, and an output variable, usually known as the response variable. In regression analysis, the model is

$$Z_i = \beta' X_i + \sigma \epsilon_i, \tag{2.1}$$

where Z_i is the response, β is a $p \times 1$ vector of parameters, X_i is a $p \times 1$ [1] vector of predictor variables, σ is a scale parameter, and ϵ_i is a random error term with distribution function

[1] For simplicity of notation, the first element of X_i is assumed to be identically 1. With this formulation, the right hand side of 2.1 includes an additive term that is analogous to the intercept term in traditional regression

Figure 2: Neural Network (line) and Randomly Generated Values (scatter) versus x



F and density function f. The covariate vector, X_i, is hypothesized to have an additive relationship to the outcome Z_i [2].

While properties of such a regression model are well known and parameter estimates are straightforward to obtain, the model in equation 2.1 is often inappropriate due to model misspecification. The primary misspecification issue is the additivity in the mean structure. An alternative to the linear model is a mean structure with a more general formulation.

In order to employ a neural network model, replace the linear mean structure, $\beta' X_i$, in equation 2.1 with a more general mean function, $h(\theta, X_i)$, as

$$Z_i = h(\theta, X_i) + \sigma\epsilon_i. \tag{2.2}$$

Here, h is an arbitrary function with a univariate response and θ is a parameter vector corresponding to the mean structure being fit. By choosing h properly, we can represent many feed-forward network architectures with equation 2.2. We will restrict our attention to feed-forward neural networks with a single hidden layer. Our methods generalize to multiple hidden layers without much difficulty.

For a feed-forward neural network with one hidden layer, specify

$$h(\theta, x) = f(\alpha_0 + \sum_{j=1}^{H} \alpha_j s_j(\beta_j' x)). \tag{2.3}$$

In this equation, $\alpha_0, ..., \alpha_H$ are scalars, $\beta_1, ..., \beta_H$ are p x 1 vectors, H is the number of nodes in the hidden layer, f is known as the activation function of the ouput layer, $s_j(.)$ are known as the activation functions for the hidden layer, and $\theta = \{\alpha_0, ..., \alpha_H, \beta_1', ..., \beta_H'\}'$ is the vector of all parameters in the neural network. For the work presented in this paper, $f(x) = x$ is assumed to be the identity function and $s_1(x) = ... = s_H(x)$ are all assumed to be equal. Using the same activation functions for $s_1, ..., s_H$ is common in most neural network literature, but this is not necessary. Some commonly chosen activation functions are linear ($s(x) = ax + b$) and logistic ($s(x) = [1 + \exp(-x)]^{-1}$). The reader should note that

[2]With the formulation of equation 2.1, interactions between and transformations of the input variables are represented as additional covariates.

this model is a special case of projection pursuit regression which is described in (Huber 1985).

If all of the activation functions in the hidden layer $s_1, ..., s_H$ are set to the identity function, this procedure is equivalent to traditional regression analysis. In this setting, many of the parameters in the neural network will not be identifiable, but the equation can be reduced to identifiable elements that are equivalent to regression parameters.

The neural network's ability to represent complex relationships between the input values and the output value is derived through the activation functions. By taking linear combinations of simple nonlinear functions, it is possible to represent complex relationships. By coupling this ability with multiple projections (linear combinations) of the input variables onto the hidden layer, the nonlinear relationships and interactions can be represented by the network structure.

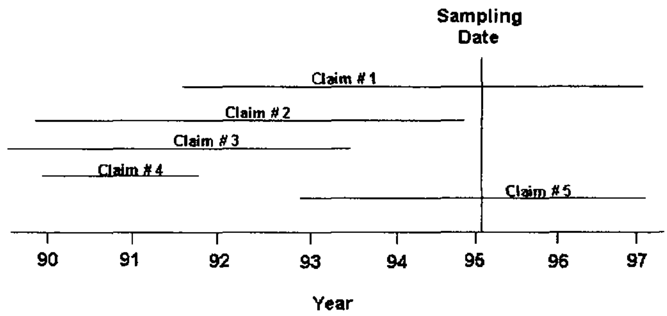
Using Equation 2.2, we can develop a likelihood equation for the data when a form is specified for the error distribution, F. In the next section, we will use this formulation to generalize the back-propagation algorithm to accommodate right-censored data.

2.1 Parametric Estimation

Let $T_1, ..., T_n$ represent a random sample of claim durations and let $O_1, ..., O_n$ represent the associated injury dates for the claims. Define the sampling date as S_0. The associated fixed censoring times for each claim are $C_i = S_0 - O_i$. We observe $Y_i = \min(T_i, C_i)$. If a claim is open, $Y_i = C_i$, otherwise, $Y_i = T_i$. Censoring is represented by an indicator variable $\delta_i = I(Y_i = T_i)$. If $\delta_i = 1$ the claim is uncensored and if $\delta_i = 0$, the claim is censored. Let $X_i = (X_{1i}, ..., X_{pi})'$ represent the p x 1 vector of covariates, or claim attributes, for the i^{th} individual.

Censored regression techniques are developed under the assumption that T_i is independent of C_i conditional on X_i. We consider C_i to be a fixed censoring time since our samples are collected at a fixed point in time. When the censoring variable is considered fixed, but each individual's censoring time can be different, then the censoring is often referred to as

Figure 3: Diagram of Sample Worker's Compensation Claims



generalized Type I censoring. The independence assumption is satisfied when T_i is independent of O_i conditional on X_i. This assumption implies that any association the duration of claim has with injury date is explained by the covariates.

Consider the following situation to illustrate the notation. Suppose we sample on a particular day, say January 31, 1995. In our notation, January 31, 1995 minus the injury date, is the censoring time. Since each claim has a different injury date, they have different censoring times. The situation is depicted for five sample claims in Figure 3. In Figure 3, claims 2, 3, and 4 are uncensored, while claims 1 and 5 are censored. We have partial information on the censored claims and would have technical difficulties accurately calculating the mean duration of a claim without incorporating censored data analysis techniques.

Let $\Theta = (\theta', \sigma)$ be the complete vector of model parameters. In equation 2.2, let $Z_i = \log(T_i)$ and $e_i = (Z_i - h(\theta, X_i))/\sigma$. If ϵ has a standard normal distribution, then the likelihood of the data is

$$L(\Theta) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \left[\exp\left(-\frac{1}{2}e_i^2\right)\right]^{\delta_i} \left[\int_{e_i}^{\infty} e^{-\frac{1}{2}u^2} du\right]^{1-\delta_i}.$$

With maximum likelihood estimation, estimates of members of the parameter vector, Θ, will be those values which maximize L.

Rather than maximizing L, it is generally easier to maximize the log likelihood, $l(\Theta)$.

$$l(\Theta) = log(L(\Theta)) = -\sum_{i=1}^{n}\left[\frac{1}{2}\log(2\pi\sigma^2) + \frac{1}{2}\delta_i e_i^2 - (1-\delta_i)\log\left(\int_{e_i}^{\infty} e^{-\frac{1}{2}u^2} du\right)\right].$$

For the back-propagation algorithm, typically a cost function is used for estimation that represents the amount of prediction error in our model. This cost function is minimized to obtain estimates of the model parameters. To accommodate right-censored data, we propose using the negative of the log likelihood as the cost function for parameter estimation.

$$C(\Theta) = \sum_{i=1}^{n}\left[\frac{1}{2}\log(2\pi\sigma^2) + \frac{1}{2}\delta_i e_i^2 - (1-\delta_i)\log\left(\int_{e_i}^{\infty} e^{-\frac{1}{2}u^2} du\right)\right]. \qquad (2.4)$$

If all of the data in equation 2.4 are uncensored and f represents the normal density, equation 2.4 can be written as

$$\begin{aligned} C(\Theta) &= \sum_{i=1}^{n}\frac{1}{2}\log(2\pi\sigma^2) + \frac{1}{2}\left(\frac{Z_i - h(X_i,\theta)}{\sigma}\right)^2 & (2.5)\\ &= \frac{n}{2}\log(2\pi) + n\log(\sigma) + \frac{1}{2\sigma^2}\sum_{i=1}^{n}(Z_i - h(X_i,\theta))^2. & (2.6)\end{aligned}$$

The first two terms on the right-hand side of equation 2.6 do not depend on θ and the value of θ which minimizes the third term will be the same for all values $\sigma > 0$. Therefore, the value of θ which minimizes $C(\Theta)$ is the same θ which minimizes

$$C_1(\Theta) = \sum_{i=1}^{n}(Z_i - h(X_i,\theta))^2. \qquad (2.7)$$

This θ is known as the least squares estimate and $C_1(\Theta)$ is the cost function typically used in fitting feed-forward neural networks without censored data. Thus, the proposed cost function given by equation 2.4 provides a generalization to the standard back-propagation algorithm for fitting feed-forward neural networks.

2.2 Numerical Estimation Procedures

Minimization of equation 2.4 can be performed with a variety of algorithms. We propose the back-propagation algorithm because it has proven successful for fitting neural network mean structures. Unfortunately, since $C(\Theta)$ is not differentiable with respect to σ at $\sigma = 0$, the algorithm does not perform adequately for estimating σ. Therefore, we employ a two-step estimation approach with θ being estimated using back-propagation and σ being estimated using maximum likelihood.

The back-propagation algorithm is related to the gradient-descent algorithm and can be found in its general form in many neural network textbooks (see for example (Hecht-Nielsen 1990)). The algorithm minimizes $C(\Theta)$ with respect to the parameter θ while considering σ to be fixed. Unlike traditional optimization routines, estimates are typically updated one observation at a time. The model parameters are updated for the i^{th} observation and the p^{th} iteration by the following updating mechanism:

$$\theta_{i+n(p-1)} = \theta_{i-1+n(p-1)} + \Delta\theta_{i-1+n(p-1)}, \tag{2.8}$$

where

$$\Delta\theta_{i-1+n(p-1)} = \lambda\nabla_\theta C_i(\theta_{i-1+n(p-1)}, \sigma),$$

λ is known as the learning rate, and $C_i()$ represents the i^{th} term in the summation of equation 2.4, and $\nabla_\theta C_i()$ is the partial derivative of $C_i()$ with respect to θ. The reader should note that the parameter estimates (network weights) are updated at each observation. Typical values for λ range from 0.0001 to 0.1 and are typically chosen by trial and error methods.

This defines the basic version of the back-propagation algorithm. Many modifications for adjusting the learning rate, λ, for estimating the parameters have been proposed. The learning rate is typically decreased if there is an increase in the cost function through one pass of the data. For more details on this algorithm see (Wasserman 1989).

We assume that σ is fixed through each pass of the data. After each pass through the data, σ is re-estimated using maximum-likelihood techniques treating θ as fixed. Considering θ to be fixed, we estimate σ by using the Newton-Raphson algorithm

$$\sigma_{j+1} = \sigma_j - [\nabla^2_\sigma C(\theta, \sigma_j)]^{-1}\nabla_\sigma C(\theta, \sigma_j). \tag{2.9}$$

This procedure can be initialized by choosing σ_0 to be the previous value of σ or by using

$$\sigma_0 = \sqrt{\frac{\sum_{i=1}^n (Z_i - h(\theta, X_i))^2}{n}},$$

where θ represents the most recent value for the Θ parameters. The reader should note that choosing a good initial value for σ is crucial for the stability of our algorithm [3]

3 Example of a Neural Network With Simulated Data

In this section an example with simulated data is used to demonstrate the prediction potential of neural networks. In this example, simulated data were used so we could reconstruct the true values that would be censored in a real data set. This example will provide some indication of the accuracy of our proposed methods for prediction.

For this example, we randomly generated data from a model with true values distributed as

$$T_i = \exp(x_i^2 + 0.5 * \epsilon_{1i}),$$

and censoring values distributed as

$$C_i = \exp(0.25 + x_i^2 + 0.5 * \epsilon_{2i}),$$

where ϵ_{1i} and ϵ_{2i} are deviates from a standard normal distribution and X_i is a uniform random deviate on the interval $(-3, 3)$. We consider the minimum of these two quantities, $Y_i = \min(T_i, C_i)$, to be the observation when censoring is present.

Both T_i and C_i follow log-normal distributions conditional on X_i. To see this, note that

$$\begin{aligned} \log(T_i) &= X_i^2 + \epsilon_{1i} \quad \text{and} \\ \log(C_i) &= X_i^2 + \epsilon_{2i}, \end{aligned}$$

where

$$\begin{aligned} \epsilon_{1i} &\sim N(0, 0.25) \quad \text{and} \\ \epsilon_{2i} &\sim N(0.25, 0.25). \end{aligned}$$

[3] The Newton-Raphson procedure still contains derivatives of $C(\Theta)$ with respect to σ. Therefore, it will experience similar problems near $\sigma = 0$. We have found that with a good starting value, this problem is minimized and the above algorithm is reasonably stable.

Thus, conditional on X_i,

$$\begin{aligned}\log(T_i) &\sim N(X_i^2, 0.25) \quad \text{and} \\ \log(C_i) &\sim N(X_i^2 + 0.25, 0.25).\end{aligned}$$

We generated 1000 observations and achieved approximately 35% censoring. This level of censoring is moderately heavy. We fit this data with the algorithms described in section 2.2. The architecture employed was a five-node, feed-forward neural network with a single hidden layer and normally distributed error terms. This network can be described with the following model equation,

$$\log(T) = \alpha_0 + \sum_{j=1}^{5} \alpha_j s(\beta_{0j} + \beta_{1j} X) + \sigma\epsilon.$$

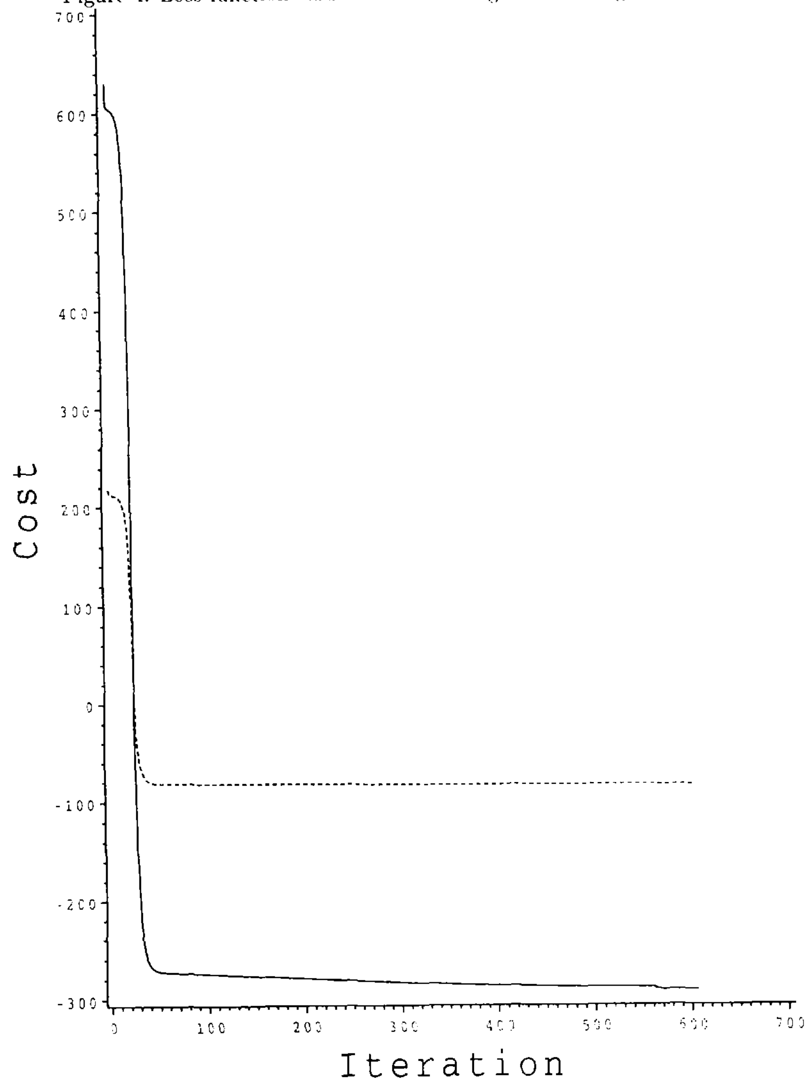
In this equation $s(u) = [1 + exp(-u)]^{-1}$ is the logistic function, and epsilon has a standard normal distribution.

Our data set of 1000 observations was split randomly into two parts with approximately 75% in the training set and 25% in the testing set. The data in the training set were used to fit or "train" the network. The data in the test set were used to assess or "test" the network's predictive abilities. Historically, the 75/25 split has been found to be adequate in most circumstances and is the common choice for training networks, but this choice is somewhat arbitrary.

The graph in Figure 4 shows values for the cost equation 2.4 plotted against p from equation 2.8 for the training set and the testing set. The algorithm described by equations 2.8 and 2.9 was applied to the training set only. In this graph the dashed lines (- - - -) represent the loss function calculated on the testing set and the solid line (——–) represents the cost function calculated on the training set. Convergence was considered obtained when the testing set's cost function failed to decrease for 40 consecutive iterations. The point at which the testing set's cost function stopped decreasing was considered the convergence point. This approach guards against the dangers of over fitting that can occur in over-parameterized models.

After the neural network model was fit, we reconstructed the log predictions and plotted them against the log of the true observations $\log(T_i)$ for the test set. Figure 5 shows a plot of

Figure 4: Loss function values for the testing and training data sets



the estimated relationship between x and $E(\log(T)|x)$ (shown by the solid line) superimposed on a scatter plot of the log of the true values, T_i. With this comparison, we demonstrate the ability of neural networks to produce accurate predictions of true values even with censoring.

4 Application of Neural Networks to Workers' Compensation Data

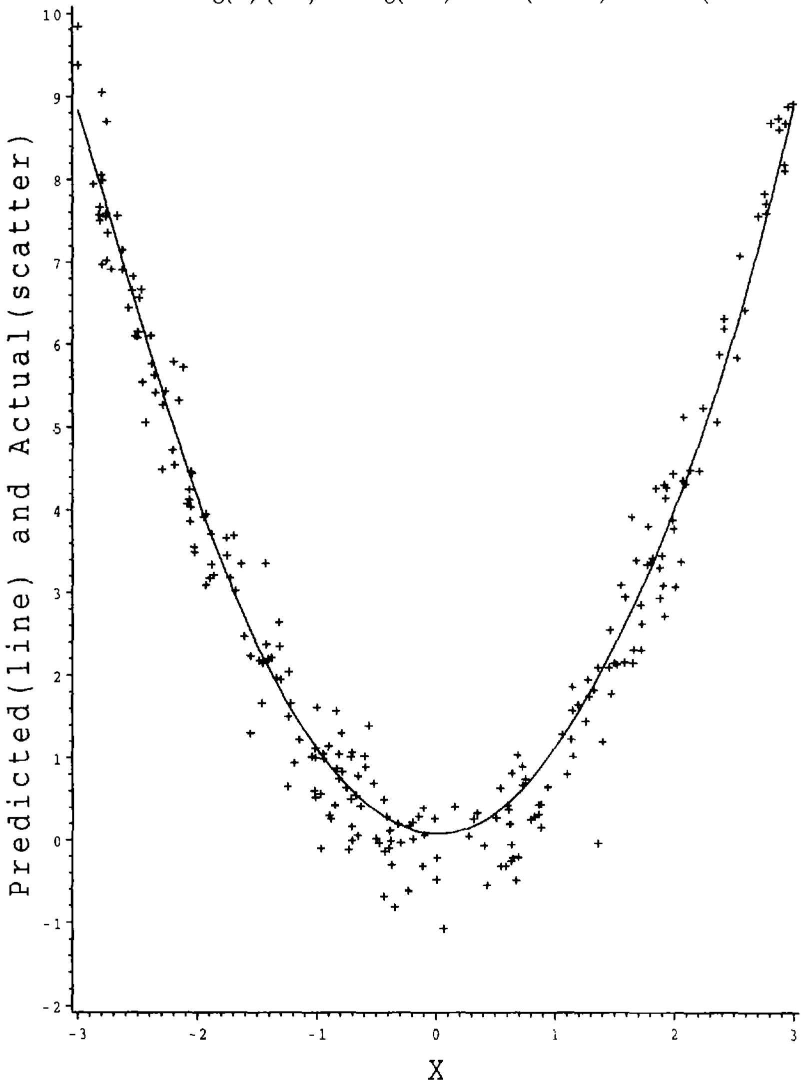
In this section we apply the methods outlined in this paper to a single state insurance carrier. Our data set consisted of all claims that opened after December 31, 1987. The data were sampled in June of 1997 and all claims that were open at that time are considered to be right censored. We construct a prediction model for estimating the duration on an individual claim with data containing right-censored observations.

Our prediction model uses several covariates that are typically available early on in a claim's life so that our models will be valid from the beginning of a claim. The characteristics used for the model are accident code, gender, weekly wage, zip code, injury type, class code, body part, nature of injury, and age at the time of injury. Accident code, injury type, class code, body part, and nature of injury variables are encoded using the National Council on Compensation Insurance (NCCI) standards.

The duration of a claim is considered to be the duration since the claim was reported to the insurance carrier. Only claims with indemnity payments were used in modeling and claims with permanent total disabilities were excluded since they typically last until a claimant is deceased. The assumptions on the distribution of the error term and censoring mechanism are defined in section 2.1.

Figure 6 demonstrates the ratio of the neural network model prediction to the actual duration against the actual duration in days. The axes are displayed in log-base 10 increments. For open cases, the duration to date was used in the plot. If all predictions are perfect, the cloud of points would lie directly on the line "1/1." Typically, the model under-predicts long duration claims and over-predicts short duration claims. The plot demonstrates that most

Figure 5: Predictions of log(T) (line) and log(true) values (scatter) versus x (test set only)



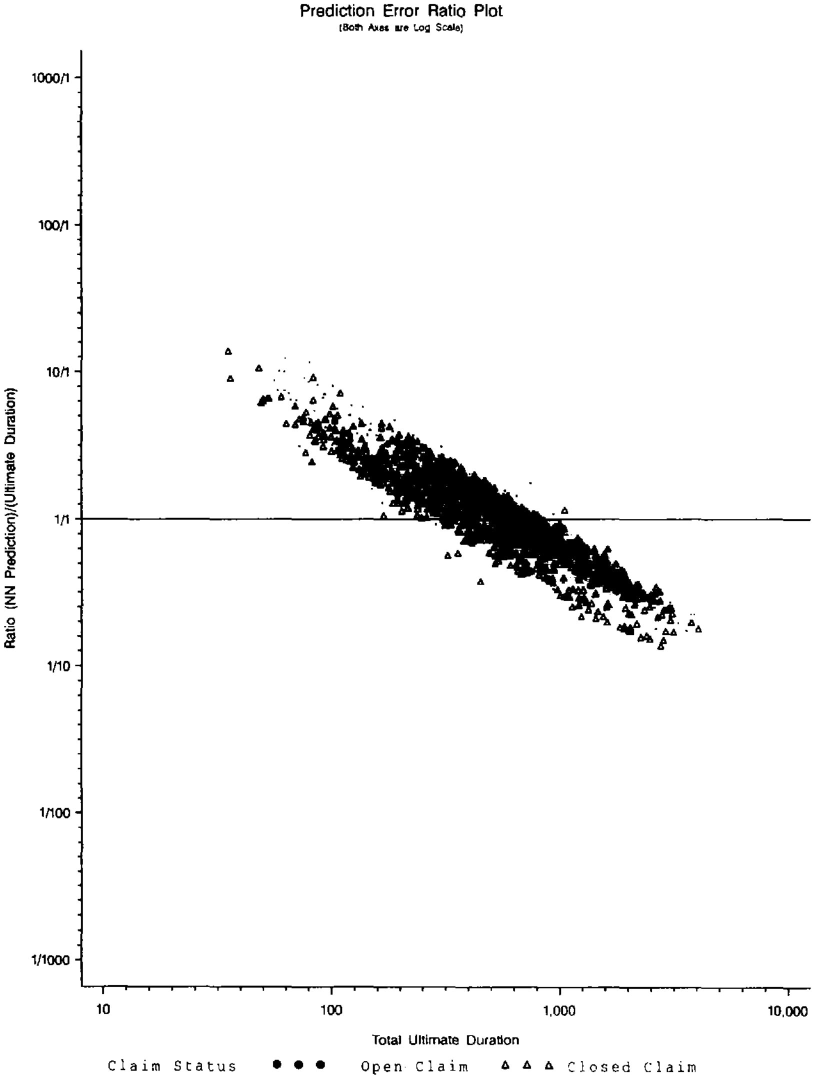
predicted durations are reasonably close to the actual duration.

5 Conclusions

This paper presented a generalization of a commonly used algorithm for neural networks using a likelihood-based approach. A connection between this algorithm and the typical least squares approach to estimation was demonstrated. We showed that our algorithm could make accurate predictions in the presence of right-censored data. The example with the simulated data demonstrated the ability of neural networks to identify nonlinear relationships even in the presence of right censoring. The example from workers' compensation insurance showed how this method can be applied to estimating duration in the presence of many covariates.

The ideas presented in this paper are general in nature and there are many other applications that could benefit from these techniques. We merely scratched the surface of possible applications. Neural networks have proven very useful in modeling complex situations. By adding a generalization to handle the problem of right censoring, this powerful technique can be applied to a new range of actuarial problems.

Figure 6: Error ratio plot. (prediction)/(actual duration) versus actual duration



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Remittance Imaging at Allstate Insurance Company

Lindsay F. Taylor

Remittance Imaging
at Allstate Insurance Company

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October, 1998

Executive Summary

The Allstate Insurance Company has implemented a process for indexing and archiving large volumes of remittance items (checks and payment coupons) via electronic image. Utilizing existing remittance processing equipment for image capture, third party software for indexing and image archive management, and existing Automated Cartridge Libraries and high-density tape media for mass storage of document images, Allstate eliminated microfilm for the viewing of premium check images. The new process has also enabled on-line, enterprise-wide viewing of checks images from any network-attached workstation running the third party image viewing software.

Benefits realized from the check imaging application include:

- a reduction of 12 people country-wide
- faster access for on-line viewing of checks
- improved reliability and security for the storage of check images
- significant savings over 5 years

Background Information

Company Organization

Allstate Insurance Company is headquartered in Northbrook, Illinois. Policy and claim processing is handled by three Data Centers. Each Data Center houses a Money Management Center (MMC) which processes premium payments for the company. Approximately 150,000 checks and a like number of bills are processed daily by each Money Management Center.

Production Environment

In 1992 Allstate installed new remittance processing equipment. This new equipment used image technology to process bills and checks. However, there was no provision for creating an electronic long-term archive of the items being processed. Long-term retention of these documents is necessary to investigate questions concerning premium payments.

Even though an electronic image of each document was being captured, only the most recent 3 days were retained due to the high storage costs on the MMC LAN server (each Data Center was generating approximately 1 gigabyte of image data to be managed and stored each day). There was no ability to transport these captured images to another platform for storage. Instead, microfilm of the processed items was created for long-term document storage.

Approach

While the remittance microfilm met the basic retention requirements, there were some obvious limitations:

- the high cost associated with the development of the microfilm
- limited access to document archives (limited number of microfilm readers)
- look-up time (an average of 15 minutes to locate a document on microfilm)
- microfilm documents not shareable between offices
- no backup or disaster recovery for the microfilm
- ongoing maintenance for the microfilm readers

By 1995, new high-density tape technology became available that allowed Allstate to leverage their existing investment in automated cartridge libraries as well as in-house mainframe processing environment to drive the storage costs of remittance images down to a cost-effective level.

Most vendors proposed the use of optical disk jukeboxes to solve our storage problem. However, we identified many disadvantages to the optical disk jukebox solution, including:

- daily maintenance required for moving media in and out of the jukebox
- relative high cost of optical disk media
- relatively limited storage space within the jukeboxes
- limited users at one time
- technology upgrades needed each year
- industry changes in optical disk standards may make archive formats obsolete (and unsupported by the vendor)
- this solution did not utilize our existing infrastructure that was already in place for large scale data storage (automated cartridge libraries)

A vendor was identified that could provide a software solution that would use our current infrastructure (DASD and mainframe tape) for the storage and management of large numbers of check images. The vendor offered a software package that would take our images, create a set of indices for each image, and archive the images for long-term storage. These archives could be maintained either on DASD for quick retrieval or on mainframe tape for cost-effective long-term storage.

However, there was still an outstanding issue concerning the number of tapes that would be required to maintain the long-term archives of check images. Given the expected volumes, each Data Center would be creating approximately one standard 36-track tape of check images each processing day. For this application, the required retention period ranged from seven years to permanent storage, depending on state and local requirements. Over several years, the maintenance required for thousands of volumes of check image tapes would have become cumbersome, and additional hardware might have been required to expand our automated cartridge libraries to accommodate this growth.

Fortunately, at about the same time as our investigation, our tape storage system vendor was developing a cartridge tape format that could hold as much as 50 to 100 times more data than our current tape format. This new format would allow us to condense our deep archives for check images by a 50 to 1 ratio, minimizing tape handling and maximizing the storage capacity of our automated cartridge libraries.

There was a consensus that this combination of third party software, mainframe tape technology, and our existing processing capacity would provide a cost-effective solution with all of the functionality required for the archival of check images. In addition, it was thought that this solution may provide the core to a much broader image and document archive. The project was approved in July, 1996.

User Requirements

During the initial discussions with the primary user groups, requirements were collected in terms of volumes to be archived, numbers of document retrievals, changes in retrieval patterns over time, retention requirements, etc. In addition, the existing technology infrastructure and information technology skill set was assessed to determine solution requirements. The following is a summary of access requirements identified for the check imaging project:

- *100% Image Capture* - all documents processed on the remittance equipment to be imaged

- *Image Manipulation* - solution must provide the user with the capability to change the size and direction of the image while viewing

- *Indices* - customer payments to be indexed by date, policy number, dollar amount, batch number, bank routing number, and pocket cut number

- *Image Availability* - solution requires the ability for enterprise-wide viewing of MMC processed checks - view any image, stored in any of the three Data Centers, from any workstation

- *Scale-ability* - solution must reflect an open architecture design that can be enhanced and increased in size and scope as we increase the number of users as well as expand the data storage types

- *Access* - solution must provide access from any standard configuration workstation in the enterprise (given proper security and access controls)

- *Cost-Effectiveness* - solution must not add any to the bottom line expense total, and reduce expenses if possible

- *Leverage Existing Technology* - wherever possible, the solution selected should leverage any suitable existing technology already in place, i.e., automated cartridge libraries, mainframe systems, Wide Area Network, Local Area Network, etc.

Implementation

The software to index and archive the images was purchased and installed in one of the three Data Centers in October 1996. By January 1997, all of the acceptance criteria was met by the vendor. The software was installed in the remaining two Data Centers later in 1997.

Each implementation went smoothly with a minimum disruption to the users. A few adjustments were required to the original design plan and were accomplished with a minimum amount of effort:

1) The network infrastructure between the MMC LAN and the mainframe needed to be upgraded due to the high bandwidth requirements of the image archival
2) The storage model was changed from a 2-tier (DASD and high-density tape) to a 3-tier design (due to the high demand for retrievals on the high density tape media). In addition to DASD and high-density tape, standard 36-track tape was added to take advantage of the 40+ tape transports available for image viewing. In addition, the seek time on a 1 gigabyte 36-track cartridge was found to be more acceptable for the high-access rate recent archives. The 50 gigabyte high-density tape media was found to be better suited for deep archive - mass volumes of images retained indefinitely.

User training on the third party desktop image viewing software went very smoothly. User training averaged an hour per user. Feedback from the users has been that the viewer is easy to use and met all image viewing needs.

Results

Everything we do at Allstate is measured in terms of impact to these constituent groups: **the customer, the shareholder, and the employee.**

The insured is **our customer** and the reason we are in business. The check imaging project has had a positive impact on the customer in two very real and tangible ways. First, it has had a significant positive impact on customer service. Customer payment inquires that used to take days to research and resolve, now take only minutes. Employees now have on-line access to check images from the desks and bottle-necks at the microfiche viewers have been eliminated. Image quality is improved and it is now easier to see the details on the check image for both the customer service representative and the customer.

Secondly, image availability was improved. The previous process required microfilm to be developed overnight and was available the following day. The new process allows images to be viewed the same day that they are processed. Also, the same image can be viewed by multiple users simultaneously. Finally, the check image solution has driven costs out of the system (more on this to follow). Lower operating costs leads to a lower expense ratio, which translates to a more competitive price for our product and additional value to the customer.

An equally important constituent is the **shareholder**. Allstate is a publicly held company. It is important for us to continue to find ways to provide additional value to our shareholder. Lower expenses, competitive pricing, and increased levels of customer service drive business results in a direction that is beneficial to our shareholders. The check imaging project, while reducing costs and improving service levels to our customers, will help us attain business results that meet our shareholder expectations.

The third constituent group is **our employees**. Our employees are the vital link that ties business objectives to our customers and our results. The check imaging application has had the following positive effects on our employees:

- increased employee productivity
- access to check images from employee desktops
- elimination of delays in waiting for an available microfilm reader
- human resource savings have created the opportunity for employees to pursue alternative career paths within the company
- increased employee satisfaction by eliminating barriers to getting their jobs done quickly and efficiently

Feedback from the employees using the check imaging system has been overwhelmingly positive. The image viewing application is easy to learn and easy to use and has improved employee productivity and employee satisfaction levels.

Summary

The Remittance Imaging Application at Allstate has provided significant benefits to the corporation. The application has met functional and performance requirements and has provided a foundation for other applications that require mass document indexing and storage capabilities.

The United States Postal Service's New Role: Territorial Ratemaking

Geoffrey Werner, FCAS, MAAA

THE UNITED STATES POSTAL SERVICE'S NEW ROLE: TERRITORIAL RATEMAKING

Geoffrey Werner, FCAS, MAAA

Abstract

For many years actuaries have recognized the importance of location as a major determinant of risk. Recently, new methodologies have been developed to better utilize geographic information systems (GIS) for territorial ratemaking. These new models generally require data assigned to a unit of geography (e.g., zip code, county, or latitude/longitude). Each unit of geography has specific advantages and disadvantages associated with it. A recent CAS survey verified zip codes are the most prevalent geographic unit used in the industry today. Unfortunately, zip codes possess a very undesirable characteristic: they are not static. This paper explores some of the issues that arise when creating, maintaining, and analyzing territorial boundaries and relativities based on zip codes.

I want to thank Robert Kane, Jason Martin, Chris Norman, and Joe Sterling. It was this small group that helped to identify the problems and to develop the solutions outlined in this paper.

THE UNITED STATES POSTAL SERVICE'S NEW ROLE: TERRITORIAL RATEMAKING

INTRODUCTION

For many years actuaries have recognized the importance of location as a major determinant of risk. In fact, according to a 1982 AIRAC study, territorial ratemaking dates back to the beginning of the twentieth century.[1] At first, the territories were selected based on limited data and a lot of judgement. Today data is more plentiful and many models have and are being developed to better analyze the data using the latest geographic information systems (GIS) technology.

In 1996 the CAS Ratemaking Call Paper Program produced two papers on territorial ratemaking: "Geographic Rating of Individual Risk Transfer Costs without Territorial Boundaries" by Randall Brubaker and "Using a Geographic Information System to Identify Territory Boundaries" by Debra Werland and Steven Christopherson. These papers helped bring territorial boundary ratemaking into the new GIS era.

Both of these models require data assigned to a unit of geography. Brubaker's model requires the most refined level of detail, latitude and longitude. His model uses the data to assign appropriate geographically-based rates to predetermined grid points. Interpolation of grid points is then used to determine the appropriate rate for a given location.[2] The Werland/Christopherson model assigns loss experience to zip codes. Due to credibility concerns, each of the zip code's loss experience is augmented with the data from nearby zips as necessary. Similar zip codes are then clustered to create territories.[3]

The aforementioned models utilize two of the units of geography being used today for territorial ratemaking. Reviews of rate filings and discussions with GIS specialists reveal a more comprehensive list of geographic units to which data can be assigned. The following choices are used individually or in combination: counties, cities/townships, zip codes (five- or nine-digit), census tracts, latitude/longitude, and areas bounded by visible markers such as streets, rivers, railroads, etc. Each of these units of areas has advantages and disadvantages. This paper will focus on the disadvantages of choosing a unit that changes over time. Specifically, the paper will focus on zip code changes as zip codes are commonly used and change more frequently than the other units. However, the comments apply to any unit susceptible to change.

GEOGRAPHIC RISK UNIT CONSIDERATIONS

There are a variety of considerations when deciding which geographic risk unit to use for territorial ratemaking:

- The unit must be small enough to be homogeneous with respect to geographic risk.
- It should be large enough to produce credible results.

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[1] Geographical Differences in Automobile Insurance, AIRAC, October, 1982.
[2] Brubaker, Randall E., "Geographic Rating of Individual Risk Transfer Without Territorial Boundaries," Casualty Actuarial Forum, Winter 1996.
[3] Christopherson, Stephen and Werland, Debra L., "Using a Geographic Information System to Identify Territory Boundaries," Casualty Actuarial Forum, Winter 1996.

- The collected premium and loss data should be easily assigned to the chosen unit.
- All competitive and/or external data should be easily mapped to it.
- It should be easy for the insured and company personnel to understand.
- The unit must be politically acceptable.
- The unit should be verifiable.
- It should not change over time.

While the paper will focus on the last criterion, Appendix A contains a short discussion about each one.

As Randall Brubaker pointed out in "Geo-coding Descriptions and Uses" latitude and longitude is the ideal as these geographical measurements are fixed (i.e., they only change if the tectonic plates shift and this is a relatively minor issue).[4] At this time, most companies do not carry that level of detail. While software is available that establishes the latitude and longitude given a street address, many actuaries may not have access to street addresses or the companies may not be able to expand their databases to carry the latitude and longitude.

The Winter 1997 Casualty Actuarial Society Forum included the results of the "1996 CAS Geo-coding Survey". Thirty-one percent of the respondents reported using geo-coded data for the definition of rating territories. When surveyed which type of geo-coded data was used for this purpose, zip code data was the most popular response. Unfortunately, as three of the respondents pointed out, zip codes can create problems because of their propensity to change.[5]

The actuary should keep in mind zip codes were created to be a label to aid in mail delivery. As zip codes were not intended to be used for data aggregation, there are issues that need to be resolved before using them for risk analysis. For example, some locations unrelated to risk can have a zip code (e.g., post office boxes), zip codes are not always easily mapped polygons, and zip codes can and do change. As mentioned previously, this paper will concentrate on the last problem. Zip codes are continually being added, deleted, and modified. And, these changes can take many forms; for example, an added zip code may include area from one existing zip code or may be formed from multiple existing zip codes. According to Joe Sterling, a GIS specialist at USAA, "any type of zip code change imaginable has probably already happened."

Unless the reader has worked extensively with location-based rating, the importance of these changes may not be obvious. There are two ways changes in the unit of area create problems: the rating of policies and data aggregation/future analysis. Remember, while the focus is on zip codes, the issues discussed apply to any geographic unit that is susceptible to change.

SETTING THE STAGE

The following is a very simplified example designed to illustrate the problems caused by zip code changes when the company defines territories using zips. This example will be used throughout the paper:

- A fictitious company defines rating territories solely by zip codes.

[4] Brubaker, Randall E., " Geo-coding Descriptions and Uses," 1997 Call Paper Program on Data Management/Data Quality, Casualty Actuarial Society.
[5] "1996 CAS Geo-coding Survey," Casualty Actuarial Forum, Winter 1997.

- The company has the following boundaries in place as of 1/1/94 (Appendix B, Figure 1):
  Territory 1 is comprised of zip codes A and B.
  Territory 2 is comprised of zip codes C and D.
  Territory 3 is comprised of the remaining zip codes.
- Rates are set equivalent to the true pure premium. The following chart lists the premiums and exposures:

Territory	Zip Code	Exposures	Pure Premium	Premium
1	A	1,800	$ 550	$ 550
	B	2,000	$ 550	$ 550
2	C	750	$ 495	$ 495
	D	1,450	$ 495	$ 495
3	Remainder	30,000	$ 440	$ 440

- All policies are annual and written on 1/1 of 94, 95, 96, 97, and 98.
- All losses are incurred (and the ultimate is known) on 7/1 of 94, 95, 96, 97, and 98.
- Zip code C is expanded to encompass part of zip code B on 4/1/95 (Appendix B, Figure 2).

POLICY RATING & INADVERTENT RATE CHANGES

The Issue

Turning to the example, the policy rating issue associated with zip code changes arises on the third renewal (1/1/96). In between the second (1/1/95) and third renewal (1/1/96), part of zip code B changed to zip code C. Consequently, on the third renewal, insureds in that portion of zip code C that used to be in zip code B (marked with an X in Figure 2) receive a 10% decrease ($550 to $495) courtesy of the U.S. Postal Service. Fortunately, from a customer service standpoint, the premium went down. Unfortunately, unless zip code changes are formally monitored, the premium decrease could have occurred unbeknownst to the actuary (if a computer systematically assigns rates given a zip code).

The example shown arises when one zip code is expanded to include at least part of another zip code assigned to a different territory. As mentioned earlier, there are other types of zip code changes and those changes result in different problems.

Instead of the example, assume population shifts necessitated the creation of a new zip code. Consequently, the post office created zip code E. The new zip code was completely carved out of old zip code B (Appendix B, Figure 3). There are two potential outcomes depending on the true definition of Territory 3. If Territory 3 is truly stated as a default option and receives "all remaining zip codes", then this new zip code (which was never contemplated) falls under the Territory 3 definition. Consequently, exposures in that portion of zip code B which became zip code E receive a rate decrease of 20% ($550 to $440). On the other hand, if Territory 3 actually includes a specific list of all the remaining zip codes, there will not be a filed rate for the new zip code. The definitions must be modified to include the newly added zip code. Obviously, the new zip code should be assigned to the same territory as the zip code from which it was created (B), so that there is no premium impact. While this may appear to be an easy fix, keeping up with the changes and updating the manual can be an administrative problem.

Next, assume new zip code E was created from parts of B and C (Appendix B, Figure 4). Again, if Territory 3 is generically stated as "all remaining zip codes", then zip code E will be mapped to Territory 3 and the risks previously in B and C will see decreases of 20% ($550 to $440) and 11% ($495 to $440), respectively. However, if Territory 3 is defined by a specific list of all the remaining zip codes, then a filed rate will be unavailable. The definitions must be modified to include a reference to E. Unfortunately, zip code E includes areas previously in two different territories. Consequently, the company has one of three options. First, E can be assigned to Territory 1 and Y's rate will increase 11% from $495 to $550.[6] Second, E can be assigned to Territory 2 and X's rate will decrease from 10% from $550 to $495.[7] Finally, the company can establish a new territory and charge an average rate; consequently, both X and Y will see moderate changes in premium (X a decrease and Y an increase).[8]

Finally, assume a zip code was deleted. The fact the definitions still include a reference to a non-existent zip code appears to be a minor issue for rating. The major issue depends on how the zip codes were modified to cover the area previously in that zip code. This area could have been covered by the expansion of existing zip codes or the creation of new zip codes (or a combination of both). Each of these options represents a variation of one of the prior examples.

Solution

The main point of the discussion is that a company must monitor zip code changes. If the company fails to do so, in the best case, the changes will be modifications within an existing territory and there will be no policy rating implications. In the worst case, existing zips are expanded to include pieces of another territory or new zip codes are created including pieces of multiple territories. These situations could result in "hidden" rate changes explained previously.

If the company wishes to monitor zip code changes, updates are available from the U.S. Postal Service. The U.S. Postal Service produces the Postal Bulletin biweekly and the Zip Alert quarterly. Each of these documents outlines all of the upcoming zip code changes. The company could regularly review one of these publications to make informed decisions before the zip code change becomes effective. Unfortunately, the description of the change is not always clear and will require further investigation. For example, one entry in the July 1998 Zip Alert reads "Establish a new ZIP CODE for a delivery area. Use Shawnee OK 74804 as the last line of address for a portion of the deliveries previously in ZIP CODE 74801."[9] While it is clear that 74804 has been added, it will require more investigation to determine exactly which piece of 74801 74804 replaced. Additionally, there are rare instances when the changes are not published until after the change has occurred. At this time this monitoring is a manual process unless the company uses a data vendor to monitor the changes for them.

Current GIS technology provides a more efficient option for handling this dilemma. A company can "lock" the boundary definitions as of a particular point in time. Returning to our example, the wording

[6] Y was in the portion of zip code C that is now part of newly added zip code E.
[7] X was in the portion of zip code B that is now part of newly added zip code E.
[8] If deciding between a specific or generic definition of Territory 3, the specific definition appears to be the better choice (although, the ideal solution will be proposed in the next section). The con associated with this option is that there is not a filed rate for all new zip codes; however, the definitions can be amended. If the "generic definition" option is chosen, the actuary has maximized the probability of premium dislocation as all zip codes added outside Territory 3 create premium changes.
[9] ZIP Alert, United States Postal Service, Volume 8, No. 1, July 1998.

can be amended to read:

Territory 1 is comprised of the area within zip codes A and B as of January 1994.
Territory 2 is comprised of the area within zip codes C and D as of January 1994.
Territory 3 is comprised of the remainder of the state.

This note ties the boundary definitions to the zip codes as they appeared in 1994 and not to the current zip code definitions. In essence, this "locks-in" the boundaries until the company --not the U.S. Postal Service-- opts to change them.

When using this option, a company cannot rely solely on a table of zip codes for an agent or a computer to scan. Instead the company should utilize GIS software to digitize the boundaries (based on the zip code lines in place on the selected date). Basically, digitization amounts to translating the boundaries into a set of mapped polygons defined by latitude and longitude points. Then at policy inception or renewal, given the street address, the GIS technology can assign the correct latitude/longitude point and plot the house within the correct polygon (regardless of what the current zip code boundaries are). Thus, the area's predetermined rate will be charged. This approach has been filed and approved in several states.[10]

INTERNAL DATA COLLECTION AND FUTURE REVIEWS

The Issue

Zip code changes not only impact the rating of policies, but they can also impact data collection and, consequently, future analysis. It is not hard to imagine that if a company collects and summarizes data based on territories and/or zip codes, a zip code change will cause some data aggregation issues. And, subsequently, will cause distortions in any reviews based on that data.

Returning to the example in which zip code C expands to include a portion of B (Appendix B, Figure 2), Charts 1 and 2 (in Appendix C) show summarized premium and loss data, respectively. In an effort to make it easier to follow the charts, zip code B is notationally split into B and B' and zip code C is notationally split into C and C'. The apostrophe represents that area that is switching. In other words, on 4/1/95 a portion of zip code B, connoted B', becomes part of zip code C, connoted C' (so the B' and C' represent the same geographical area before and after 4/1/95, respectively).

The distortion occurs in 1995. At the beginning of the year, zip code B exists in its entirety (Appendix B, Figure 1) and the premium is coded accordingly. On 4/1/95 zip code C is expanded to include a portion of B (Appendix B, Figure 2). This occurs before the loss in the middle of the year is coded. Thus, 1995 data is distorted as the $550 of premium is coded in zip code B (in Territory 1), but the loss in zip code C (in Territory 1)[11].

It is easy to see how this overstates the profitability of zip code B at the expense of zip code C. This distortion is exacerbated by the extra $55 ($550-$495) of unfunded loss zip code C must absorb in 1996, 1997, and 1998 as the higher risk ($550) is now being included within the lower risk area at the cheaper rate of $495. This latter phenomenon adversely impacts the profitability of Territory 2.

[10]Adoption of this solution does compromise the understandability of the definitions. In other words, discrepancies between filed and actual zip codes can cause confusion for insureds, agents/policy service personnel, and regulators; although, it does seem like a worthwhile trade-off.

[11] This assumes the claims adjuster simply corrects the address (i.e., updates the zip code), but does not change the territory. Appendix D illustrates the case in which the adjuster changes both the zip code and the territory.

Impact on Territorial Relativity Reviews

If data is summarized on the territorial level, the data will only be impacted if the zip code changes alter the boundaries (as in our example). Zip code changes are most prevalent in areas where the population is shifting. Intuitively, one would expect these shifts to be in or around the cities where the territories are the smallest thus making it more likely the zip code change will alter a territory.

There is some good news. Because the territory was not updated on the loss database when the loss data was collected, there is no impact on the territory (Territory 1) that lost part of its exposures.[12] However, as mentioned previously, Territory 2 will be impacted by the inclusion of the unfunded $55 of loss by the higher risk insured being included at the lower rate level of Territory 2. Fortunately, as in our example, the effected portion of the zip will usually be a small piece of both the original and new territories; consequently, any distortion will probably be minor. In our example (Appendix C, Chart 3) the 250 exposures that switch represent 25% of new Territory 2. Assuming that distribution of exposures, the indicated relativities for Territory 2 were only slightly overstated (.91 versus .90). In fact, those differences are so minor they would likely be eliminated if the raw indicated relativities were credibility-weighted with the current relativities or some other form of supplemental data.

Impact on Territorial Boundary Reviews

On the other hand, if zip codes change (whether it is the addition, deletion, or modification of zip codes), data summarized at the zip code level will be impacted more significantly than the data summarized at the territory level. Of course, this statement assumes that the territories are, in general, made up of multiple zip codes.

Many of the boundary review procedures utilized today assign a measure of risk to a small geographic unit (usually involving zip codes). An obvious measure of risk to assign to the zip code is the indicated relativity. In our example (Appendix C, Chart 4), the indicated relativity for B was understated by 3% (.97 versus 1.00) and the indicated relativity for C was overstated by 8% (.97 versus .90). If the piece of B that moved to C represented more (or less) exposures than 12.5% of B or 25% of C, then the impact would have been larger (or smaller).

One important note, relativities calculated at the zip code level often lack the necessary credibility to warrant full weight. Consequently, the individual zip code relativities will often be weighted with the relativities of contiguous zips. Thus, the understatement of B would be somewhat offset by the overstatement of C in the credibility-weighting procedure. Furthermore, after the zip code's credibility-weighted indicated relativity is determined, zip codes are often clustered with like zips to determine a territory. To the extent the over- or understatement is small, the clustering could likely make the issue moot.

Solution

Does the solution proposed to fix the "rating problem" also fix this problem? The answer is yes and no. By locking in the boundaries as of a specific point in time, the actuary ensures the territorial boundaries will be fixed and all exposures will remain within the originally assigned territory regardless of any zip code changes. As zip code changes will not affect data summarized at the territorial level, this does solve the territorial relativity analysis problem!

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[12] Of course, this simplified example assumes the same loss frequency and severity each year. If the years prior to the loss of exposures were significantly better (or worse) than the years after the loss, then a distortion could occur in Territory 1 also.

But no, it does not solve the issue of future boundary analysis. For the future boundary analysis, the actuary will need the data aggregated at the current zip code level to create appropriate boundaries using the most current zip codes.[13] Fortunately, there is a good solution for fixing the data for boundary analysis, too. If each of the historical records has fields populated with the street address or the correct latitude and longitude, then the actuary can use GIS software to map the historical records into the most current zip codes. Once this conversion is completed, the review can be resumed.

It is necessary to consider the situation in which the actuary does not have access to that level of detail. Fortunately--as we discovered in the prior section--the impact of changes in zip codes is probably minor; however, as stated in ASP No. 23 Data Quality, "The actuary may be aware that the data are incomplete, inaccurate, or not as appropriate as desired. In such cases, the actuary should consider whether the use of such imperfect data may produce material biases in the results of the study..."[14] To quantify the magnitude of the problem, the actuary must undergo a two-step approach. First, the actuary must identify the zip code additions, deletions, and modifications. Second, the actuary should determine whether the zip code changes would have a material impact on the analysis.

The U.S. Postal Service's Postal Bulletins and Zip Alerts represent the most accurate and complete list of changes. As mentioned earlier, the actuary can review the bulletins for the time period corresponding to the experience period to determine all of the zip code changes (with the exception of a few recent changes that may not yet be listed). This is an extremely labor-intensive process.

Without going to the U.S. Postal Service's publications, there is another much less desirable technique to identify the zip code changes that impacted a significant number of insureds. The actuary could obtain a list of current zip codes and produce a list of zip codes with the associated exposures for each of the individual years in the experience period. To identify added zip codes, the actuary should find current zip codes that do not show up in the earlier years of the experience period. To identify deleted zip codes, the actuary should find zip codes from the earlier years that do not show up in the current list of zip codes. To identify modified zip codes, the actuary should look for any zip codes that had unexplained material increases or decreases in exposures during the experience period. Looking at our example, zip code B had an unexplained 12.5% exposure decline (2,000 to 1,750) from 1995 to 1996. Further investigation uncovers the neighboring zip, C, increased by 250 exposures (33%) from 750 to 1000. By investigating the data in this manner, the actuary can not only hypothesize what type of change occurred, but can also probably determine when the change happened.[15]

Once all of the changes have been identified, the actuary should estimate the number of exposures impacted. If the number of exposures is material, then an adjustment should be attempted. The actuary should set an appropriate exposure cutoff based on a predetermined tolerance level. Scenario testing similar to the example included in this paper can help identify the different impact of zip code changes given varying levels of exposures. Additionally, the actuary should consider any further adjustments that will be made (e.g., credibility-weighting or clustering) that may further mitigate the distortion. Once the cutoff is established, the actuary can manually re-assign the old zip codes for all

[13] If the actuary wants to aggregate data into the original zip codes then the "locking-in" of boundaries technique could be used at the zip code level; however, it seems impractical to create new boundaries based on old zip codes.
[14] Actuarial Standard of Practice No. 23 Data Quality, Actuarial Standards Board, July 1993.
[15] Be forewarned this method will only uncover zip code changes that impact a significant number of insureds and really requires a stable growth environment. Unfortunately, zip codes changes seem to be most prevalent in areas where the population is not stable.

codes changes effecting more exposures than the cutoff. Once the zips are re-assigned, the review can resume.

EXTERNAL DATA

The Issue

The actuary will frequently use external data to supplement internal company loss data. Competitors' boundaries and relativities, traffic density statistics, and theft rates are examples of supplemental data currently being reviewed by actuaries when making location-based rating decisions. To be valuable for the purpose of location-based rating, this data must be assigned to some unit of geography. Most of the data used today is already summarized at the zip code, county, or census tract level.

Of course, this data is susceptible to changing definitions, too. For example, assume the actuary has Department of Transportation (DOT) data that summarizes the vehicles/square mile at the zip code level and wants to use a traffic density regression model to predict the frequency of a given zip code. If a zip code was newly created, it may not even be in the DOT data. If the actuary uses the unadjusted DOT data, the regression formula will produce a very low frequency, as the zip code will appear to have no exposures.

Similarly, competitive data can be impacted by changes in the units of geography. Referring back to the "policy rating" example, all companies are impacted by zip code changes. Assume the actuary is reviewing competitors' filed zip code-based boundaries similar to those listed earlier in the paper. If the boundaries are not recent and the U.S. Postal Service has changed zip codes in that area, the actuary may have difficulty determining where exactly the competitors' boundaries are. If zip code C is expanded to include part of zip code B (Appendix B, Figure 2), the actuary must decide if the new part of C is being charged Territory 1 or Territory 2 rates. Similarly, if zip code E is created from parts of zip codes B and C (Appendix B, Figure 4), the actuary must decide if zip code E has the rates applicable to Territory 1, 2, of 3.

In most cases this data is simply being used as supplemental data to aid in judgment decisions, and these unit changes will not have a material impact. If, however, the data is being used in formulae on a unit by unit basis, it may be more problematic (especially if the data does not have data from newly added zip codes).

The Solution

Competitive data is probably the most problematic as the actuary may not even be able to determine the applicable version of the geographic unit underlying the data. In other words, the actuary may not know (unless it is noted in the filing) whether a competitor is using the zip codes applicable in 1994 or 1995. Of course, the actuary can make an educated guess based on the date of the filing and can further narrow the choices by examining the boundary definitions for newly added zips (starting with the most recently added zip codes).

In today's world, the actuary can assume that external, non-insurance data is aggregated into the geographic units applicable to that time period. Thus, if the actuary is examining DOT traffic density data for 1994-1998, then the 1994 data is probably using zip codes applicable in 1994, the 1995 data is probably using the zip codes applicable in 1995, and so on.

If the zip code changes are minor and the data is not being directly plugged into a formula, the actuary can probably live with the unadjusted data. For example, the actuary should map the competitors' rates assuming the current zip codes. Barring a note on the competitors' manual pages to the contrary, this assumption should be correct.

If the actuary is using this data formulaically and there are significant zip code changes, he/she may want to try to cleanse the data. Presently, this appears to require a labor-intensive manual mapping. One other alternative is to combine the zip code data. The actuary can assign each zip code a value equivalent to the weighted-average of the values from that zip code and all of the contiguous zip codes. By including all of the contiguous zips, the actuary minimizes the impact of small changes in zip code boundaries. Turning to the example pictured in Figures 1 and 2 of Appendix B, all of zip code B and zip code C (as well as all other contiguous zip codes) will be included in the weighted-average. Therefore, it will not matter where the external data source maps that part of B that is switched to zip code C. Of course, this does diffuse the impact of a particular zip code's own information. The actuary must evaluate which course of action, if any, is best given the particular situation.

SUMMARY

As more and more companies acquire GIS technology and/or move away from traditional territorially-based rating, the issues associated with zip code (or any other geographic unit) changes will no longer be an issue. However, today many companies do not have the technology and are currently defining rating territories based on zip codes. Unfortunately, zip codes can and do change leading to problems for a company. If a company wants to continue to use zip codes, the actuary can choose two paths to handle these issues. He/she can laboriously track all zip code changes, regularly update the manual, and manually map all the data to perform future actuarial analysis. Alternatively, the company can acquire current GIS technology, capture the street address or latitude and longitude on each record, and "lock-in" all boundaries as of a date in time to systematically eliminate the adverse impact of the changes.

APPENDIX A

When attempting to perform boundary analysis, the actuary probably wants to assign a measure of risk to a small geographic unit. Similar small units can then be clustered to determine appropriate territories. The following is a comprehensive list of geographic units to which data can be assigned, these choices are used individually or in combination: counties, cities/townships, zip codes (five- or nine-digit), census tracts, latitude/longitude, and areas bounded by visible markers such as streets, rivers, railroads, etc. As mentioned in the paper, there are a variety of considerations when deciding which geographic risk unit to use:

- The building block must be small enough to be homogeneous with respect to geographic risk.
- The unit should be large enough to produce credible results.
- The collected company loss and premium data should be easily assigned to the chosen unit.
- All competitive and/or external data should be easily mapped to the geographical unit.
- It should be easy for the insured and company personnel to understand.
- The unit must be politically acceptable.
- The unit should be verifiable.
- The geographic unit should not change over time.

The building block must be refined enough to offer a homogenous group of risks with respect to geographic risk. A simple examination of counties around major cities indicate that county-level detail is probably not refined enough. Oftentimes these counties include both urban and suburban risks. Similarly, city-level detail is probably too heterogeneous for the major cities. Five-digit zip codes are probably the largest building blocks that will be acceptable to the actuary in most instances. The greatest common denominator of counties and zip codes, nine-digit zip codes, and census tracts are better choices. Of course, the use of latitude and longitude will allow the actuary to establish the risk unit as small as one location, thus ensuring homogeneity. The actuary can use statistical techniques (e.g., variance analysis) and/or judgement to decide which other units produce homogenous groups.

The building block should also be large enough to produce credible results. Clearly, this criterion represents a trade-off with the preceding criterion. To get around this issue, many actuaries have been using relatively small risk units and bolstering the credibility by using the data from contiguous risk units. The Brubaker[16] and Werland/Christopherson[17] methodologies both employ this type of approach.

The actuary must consider what data is available. If the insurer's databases are built such that the actuary's data is aggregated at the county level (and no further refinement is available), then the actuary may want to consider counties as an appropriate building block. Likewise, if the data is aggregated by zip codes, then zip code may be the most appropriate. If individual records with street addresses are available, then this becomes a non-issue as software is available that could map the data to any of the building blocks. Not surprisingly, the "1996 CAS Geo-coded Survey" indicates zip codes are the most common.[18]

If the actuary is going to use external, supplemental data, he/she must consider how to integrate the company experience with the external data. The two need not use the exact same geographic unit; however, one should be easily mapped to the other. For example, assume the company loss and

[16] Brubaker, Randall E., "Geographic Rating of Individual Risk Transfer Without Territorial Boundaries," Casualty Actuarial Forum, Winter 1996.

[17] Christopherson, Stephen and Werland, Debra L., "Using a Geographic Information System to Identify Territory Boundaries," Casualty Actuarial Forum, Winter 1996.

[18] "1996 CAS Geo-coding Survey," Casualty Actuarial Forum, Winter 1997.

premium experience is reported in zip code/county blocks and the external data is only available at the county level. The actuary can assign the value derived from the external data to each and every zip code/county block that makes up the county. A quick review of available data indicates that most external data is available at the five-digit zip code or county level. Thus, the greatest common denominator of counties and zip codes works well from this standpoint. Of course, latitude and longitude would allow the actuary to map any external data to the internal data.

As always, the unit must be politically acceptable. To date none of the aforementioned units appear to be unacceptable to regulators. Based on their widespread use, zip codes and counties are probably the most acceptable units. Zip codes are not only accepted in many states, but their use has even been mandated in at least two locations, California and Nebraska, for personal automobile insurance. However, early in 1998 the Washington Office of Insurance Commissioner drafted a regulation prohibiting insurers from raising rates solely because the U.S. Postal Service changes the insured's zip code.[19] Note the draft regulation did not prohibit insurers from using zip codes, it simply prohibited any increases due to zip code changes. After an initial inquiry, the Washington OIC decided not to pursue the regulation further, but we could witness similar rules in other locations.

It is always nice to utilize rating variables that are easily verifiable and easy for the insured to understand. Today's GIS software makes any of these units easily verifiable given the correct street address. Clearly, most insureds can recite the city, county, and/or zip code in which they live. On the other hand, most people are not conversant with the geographic units of latitude/longitude and census tract.

Finally, the units should not change over time. Political boundaries like zip codes and cities appear to be the worst from this standpoint. While counties are also political boundaries, they appear to be less susceptible to change than zips or cities. Census tracts change every ten years. For all practical purposes, latitude and longitude is impervious to change; consequently, it appears to be the superior choice from this standpoint.

[19] WAC 284-24-110 Effect of changes to zip code boundaries.

APPENDIX B

Figure 1: Boundaries as of 1/1/94

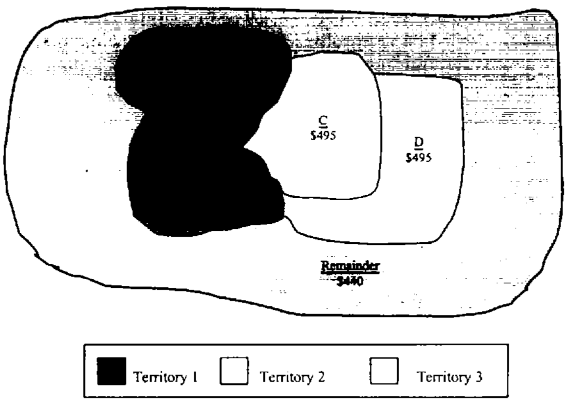
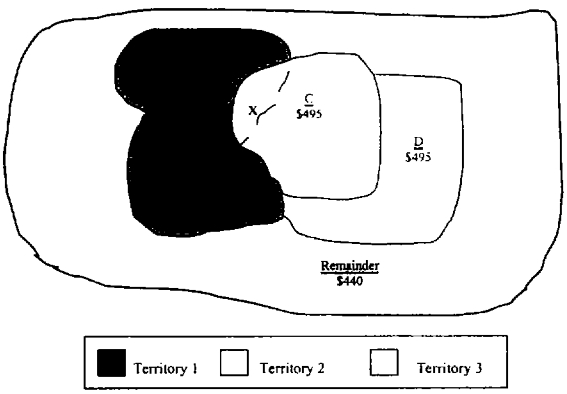


Figure 2: Boundaries as of 4/1/95. C expands into B.



APPENDIX B (Continued)

Figure 3: Boundaries as of 4/1/95, Totally enclosed new zip code.

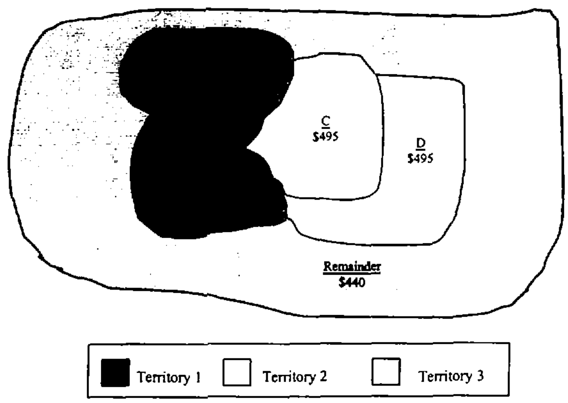
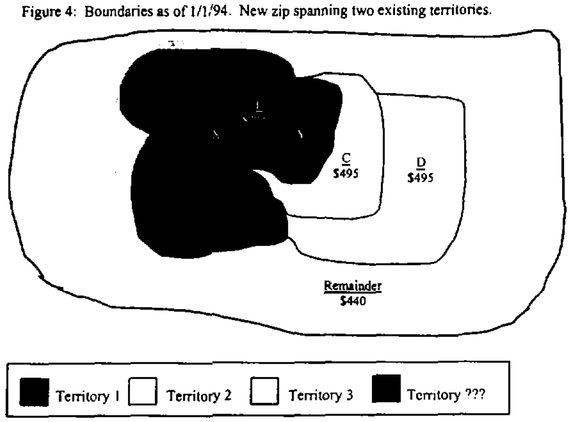


Figure 4: Boundaries as of 1/1/94. New zip spanning two existing territories.



APPENDIX C

Chart 1
SUMMARIZATION OF PREMIUM

Zip & Territory updated at 1st renewal after zip code change.

Date	Zip Code	Territory	Written Exposures	Written Premium	
1/1/94	A	1	1,800	$ 990,000	
	B	1	1,750	$ 962,500	
	B'	1	250	$ 137,500	Charged: $550
	C	2	750	$ 371,250	
	D	2	1,450	$ 717,750	
	Remainder	3	30,000	$13,200,000	
1/1/95	A	1	1,800	$ 990,000	
	B	1	1,750	$ 962,500	
	B'	1	250	$ 137,500	Charged: $550
	C	2	750	$ 371,250	
	D	2	1,450	$ 717,750	
	Remainder	3	30,000	$13,200,000	
1/1/96	A	1	1,800	$ 990,000	
	B	1	1,750	$ 962,500	
	C'	2	250	$ 123,750	Charged: $495
	C	2	750	$ 371,250	
	D	2	1,450	$ 717,750	
	Remainder	3	30,000	$13,200,000	
1/1/97	A	1	1,800	$ 990,000	
	B	1	1,750	$ 962,500	
	C'	2	250	$ 123,750	Charged: $495
	C	2	750	$ 371,250	
	D	2	1,450	$ 717,750	
	Remainder	3	30,000	$13,200,000	
1/1/98	A	1	1,800	$ 990,000	
	B	1	1,750	$ 962,500	
	C'	2	250	$ 123,750	Charged: $495
	C	2	750	$ 371,250	
	D	2	1,450	$ 717,750	
	Remainder	3	30,000	$13,200,000	
Total (By Zip Code)	A		9,000	$ 4,950,000	
	B		9,250	$ 5,087,500	
	C		4,500	$ 2,227,500	
	D		7,250	$ 3,588,750	
	Remainder		150,000	$66,000,000	
Total (By Territory)		1	18,250	$10,037,500	
		2	11,750	$ 5,816,250	
		3	150,000	$66,000,000	

APPENDIX C (Continued)

Chart 2
SUMMARIZATION OF LOSSES

Date	Zip Code	Territory	Incurred Claims	Incurred Loss
7/1/94	A	1	180	$ 990,000
	B	1	175	$ 962,500
	B'	1	25	$ 137,500
	C	2	68	$ 371,250
	D	2	131	$ 717,750
	Remainder	3	2,400	$13,200,000
7/1/95	A	1	180	$ 990,000
	B	1	175	$ 962,500
	C'	1	25	$ 137,500
	C	2	68	$ 371,250
	D	2	131	$ 717,750
	Remainder	3	2,400	$13,200,000
7/1/96	A	1	180	$ 990,000
	B	1	175	$ 962,500
	C'	2	25	$ 137,500
	C	2	68	$ 371,250
	D	2	131	$ 717,750
	Remainder	3	2,400	$13,200,000
7/1/97	A	1	180	$ 990,000
	B	1	175	$ 962,500
	C'	2	25	$ 137,500
	C	2	68	$ 371,250
	D	2	131	$ 717,750
	Remainder	3	2,400	$13,200,000
7/1/98	A	1	180	$ 990,000
	B	1	175	$ 962,500
	C'	2	25	$ 137,500
	C	2	68	$ 371,250
	D	2	131	$ 717,750
	Remainder	3	2,400	$13,200,000
Total (By Zip Code)	A		900	$ 4,950,000
	B		900	$ 4,950,000
	C		438	$ 2,406,250
	D		653	$ 3,588,750
	Remainder		12,000	$66,000,000
Total (By Territory)		1	1,825	$10,037,500
		2	1,065	$ 5,857,500
		3	12,000	$66,000,000

Zip updated at 1st loss date after zip code change.

Territory updated at 1st renewal after zip code change.

Loss: $550

Loss: $550

Loss: $550

Loss: $550

Loss: $550

APPENDIX C (Continued)

Chart 3
TERRITORIAL ANALYSIS

Territory	Exposures	Premium	Incurred Loss	Loss Ratio	Current Relativity	Proposed Relativity	Over/(Under) Stated
1	18,250	$10,037,500	$10,037,500	1.00	1.00	1.00	0%
2	11,750	$ 5,816,250	$ 5,857,500	1.01	0.90	0.91	1%
3	150,000	$66,000,000	$66,000,000	1.00	0.80	0.80	0%
Total	180,000	$81,853,750	$81,895,000	1.00	0.83		

Chart 4
ZIP CODE ANALYSIS

Zip Code	Exposures	Premium	Incurred Loss	Loss Ratio	Current Relativity	Proposed Relativity	Over/(Under) Stated
A	9,000	$ 4,950,000	$ 4,950,000	1.00	1.00	1.00	0%
B	9,250	$ 5,087,500	$ 4,950,000	0.97	1.00	0.97	(3)%
C	4,500	$ 2,227,500	$ 2,406,250	1.08	0.90	0.97	8%
D	7,250	$ 3,588,750	$ 3,588,750	1.00	0.90	0.90	0%
Remainder	150,000	$66,000,000	$66,000,000	1.00	0.80	0.80	0%
Total	180,000	$81,853,750	$81,895,000	1.00	0.83		

APPENDIX D

Appendix C displayed the situation in which the address (i.e., zip code) was updated on the loss database at the time of the loss, but not the territory. Instead, assume that the territorial number is also changed on the loss database at the time of the loss, but the premium database is unaffected until the next renewal. This does not have any additional impact on the zip code analysis, but leads to a greater distortion in the territorial relativity analysis as the 1995 premium for the portion of zip code B that is switching is coded in Territory 1 and the loss is coded in Territory 2.

Chart 1
SUMMARIZATION OF PREMIUM

	Date	Zip Code	Territory	Written Exposures	Written Premium	
	1/1/94	A	1	1,800	$ 990,000	
		B	1	1,750	$ 962,500	
		B'	1	250	$ 137,500	Charged: $550
		C	2	750	$ 371,250	
		D	2	1,450	$ 717,750	
		Remainder	3	30,000	$13,200,000	
	1/1/95	A	1	1,800	$ 990,000	
		B	1	1,750	$ 962,500	
		B'	1	250	$ 137,500	Charged: $550
		C	2	750	$ 371,250	
		D	2	1,450	$ 717,750	
		Remainder	3	30,000	$13,200,000	
	1/1/96	A	1	1,800	$ 990,000	
		B	1	1,750	$ 962,500	
Zip & Territory updated at 1st renewal after zip code change.		C'	2	250	$ 123,750	Charged: $495
		C	2	750	$ 371,250	
		D	2	1,450	$ 717,750	
		Remainder	3	30,000	$13,200,000	
	1/1/97	A	1	1,800	$ 990,000	
		B	1	1,750	$ 962,500	
		C'	2	250	$ 123,750	Charged: $495
		C	2	750	$ 371,250	
		D	2	1,450	$ 717,750	
		Remainder	3	30,000	$13,200,000	
	1/1/98	A	1	1,800	$ 990,000	
		B	1	1,750	$ 962,500	
		C'	2	250	$ 123,750	Charged: $495
		C	2	750	$ 371,250	
		D	2	1,450	$ 717,750	
		Remainder	3	30,000	$13,200,000	
	Total (By Zip Code)	A		9,000	$ 4,950,000	
		B		9,250	$ 5,087,500	
		C		4,500	$ 2,227,500	
		D		7,250	$ 3,588,750	
		Remainder		150,000	$66,000,000	
	Total (By Territory)		1	18,250	$10,037,500	
			2	11,750	$ 5,816,250	
			3	150,000	$66,000,000	

APPENDIX D (Continued)

Chart 2
SUMMARIZATION OF LOSSES

Zip & Territory updated at 1st loss date after zip code change.

Date	Zip Code	Territory	Incurred Claims	Incurred Loss	
7/1/94	A	1	180	$ 990,000	
	B	1	175	$ 962,500	
	B'	1	25	$ 137,500	Loss: $550
	C	2	68	$ 371,250	
	D	2	131	$ 717,750	
	Remainder	3	2,400	$13,200,000	
7/1/95	A	1	180	$ 990,000	
	B	1	175	$ 962,500	
	C'	2	25	$ 137,500	Loss: $550
	C	2	68	$ 371,250	
	D	2	131	$ 717,750	
	Remainder	3	2,400	$13,200,000	
7/1/96	A	1	180	$ 990,000	
	B	1	175	$ 962,500	
	C'	2	25	$ 137,500	Loss: $550
	C	2	68	$ 371,250	
	D	2	131	$ 717,750	
	Remainder	3	2,400	$13,200,000	
7/1/97	A	1	180	$ 990,000	
	B	1	175	$ 962,500	
	C'	2	25	$ 137,500	Loss: $550
	C	2	68	$ 371,250	
	D	2	131	$ 717,750	
	Remainder	3	2,400	$13,200,000	
7/1/98	A	1	180	$ 990,000	
	B	1	175	$ 962,500	
	C'	2	25	$ 137,500	Loss: $550
	C	2	68	$ 371,250	
	D	2	131	$ 717,750	
	Remainder	3	2,400	$13,200,000	
Total (By Zip Code)	A		900	$ 4,950,000	
	B		900	$ 4,950,000	
	C		438	$ 2,406,250	
	D		653	$ 3,588,750	
	Remainder		12,000	$66,000,000	
Total (By Territory)		1	1,800	$ 9,900,000	
		2	1,090	$ 5,995,000	
		3	12,000	$66,000,000	

APPENDIX D (Continued)

Chart 3
TERRITORIAL RELATIVITY ANALYSIS

Territory	Exposures	Premium	Incurred Loss	Loss Ratio	Current Relativity	Proposed Relativity	Over/(Under) Stated
1	18,250	$10,037,500	$ 9,900,000	0.99	1.00	0.99	(1)%
2	11,750	$ 5,816,250	$ 5,995,000	1.03	0.90	0.93	3%
3	150,000	$66,000,000	$66,000,000	1.00	0.80	0.80	0%
Total	180,000	$81,853,750	$81,895,000	1.00	0.83		

Chart 4
ZIP COPE ANALYSIS

Zip. Code	Exposures	Premium	Incurred Loss	Loss Ratio	Current Relativity	Proposed Relativity	Over/(Under) Stated
A	9,000	$ 4,950,000	$ 4,950,000	1.00	1.00	1.00	0%
B	9,250	$ 5,087,500	$ 4,950,000	0.97	1.00	0.97	(3)%
C	4,500	$ 2,227,500	$ 2,406,250	1.08	0.90	0.97	8%
D	7,250	$ 3,588,750	$ 3,588,750	1.00	0.90	0.90	0%
Remainder	150,000	$66,000,000	$66,000,000	1.00	0.80	0.80	0%
Total	180,000	$81,853,750	$81,895,000	1.00	0.83		

Insurance Data and Intellectual Property Issues

Alan E. Wickman, ACAS, MAAA

Insurance Data and Intellectual Property Issues

by

Alan Wickman, ACAS

Abstract

This paper provides a timely overview of the legal, political and practical implications of intellectual property concepts as they apply to insurance data collection and use.

Intellectual property issues have become common in regulatory discussions during the 1990's and have also become important to the understanding of advisory organizations. This increased interest and importance – which can be expected to intensify – is largely due to a confluence of two factors: (1) advances in information technology, especially the evolution of personal computers, and (2) a rethinking of the system of statistical agents and advisory organizations (formerly rating bureaus). An understanding of these issues requires a fundamental grasp of intellectual property concepts and an awareness of a host of conflicting considerations.

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The author wishes to thank some of those who reviewed earlier drafts of this paper. Persons that provided a significant number of suggestions included Birny Birnbaum; Anthony Grippa, FCAS; Kevin Hennosy; Dr. Robert Klein; Gary Knoble, AIDM; Jim Mallon; Mary Van Sise and Jeanette Smith, JD. Please note that most of these persons disagree with at least one or more of the statements, implications and conclusions contained in this paper.

Introduction

Perhaps the key precept of the insurance data management profession is that data is a valuable resource and must be managed as such. Paraphrased, insurance data is *intellectual property*. "Intellectual property" is also a legal term that includes such concepts as patents, trade secrets, copyrights and trademarks. The primary focus of this paper will be with the application of intellectual property concepts to statistical data[1] and to similar data contained in rate filings.

[1] Unless otherwise qualified, references to "statistical data" refer to the detailed data reported to statistical agents and databases developed from that data. The term also refers to similar data and databases in the possession of individual insurers. For purposes of this paper, however, the term "statistical data" does not refer to Annual Statement data or reports that accompany rate filings, even though they are ultimately derived from "statistical data." The distinction is important in this paper owing to legal differences that affect the disclosure and distribution of the different types of information.

Intellectual property concepts also apply (and are also the subject of controversy) with regard to such non-statistical items as underwriting guidelines, manuals, policy forms, etc.

There are unsettled situations that relate to the value of data and what is done with it once an insurer reports it to others. Primarily, this reporting is accomplished via statistical agents or advisory organizations. It may also be reported directly to state insurance departments, state accident boards (for workers' compensation) or to others[2]. While contractual agreements or laws largely control the use of insurer data by these entities, there have been changes in the ways that these institutions function and there are ongoing discussions regarding other possible changes. This paper is divided into the following sections:

- Statistical Reporting & State Insurance Regulation;
- Trade Secrets;
- Freedom of Information Act (FOIA) Considerations;
- "Ownership and Control" Issues;
- Controversies Surrounding the Disclosure of Insurer-Specific Statistical Data;
- Data Disclosure in Rate Filings;
- Intellectual Property Issues Relating to Advisory Organizations;
- Florida Workers' Compensation Initiative
- Extending the "Florida Initiative" to Other Lines and States, and
- Speculation about the Future

Statistical Reporting & State Insurance Regulation

State insurance regulation dates to the 1800's, but most of the significant events relevant to data collection and state insurance departments have occurred since 1944. From the 1800's until the mid-1940's, rates for such lines as fire and auto and casualty insurance were generally set by associations of insurers known as rating bureaus. Rating bureaus arose out of disastrous price competition by fire insurers in the early years of insurance, and were welcomed and sanctioned by the states as a means to assure solvency and orderly markets. These organizations certainly operated "in restraint of trade," but the courts of the day had not interpreted insurance as "commerce," and hence insurance was not subject to federal authority under the Constitution's "commerce clause." Specifically, federal anti-trust laws did not apply.

To the modern reader, it is almost impossible to think of insurance as anything but interstate commerce, but it remained that way until June 4, 1944 when the Supreme Court (by a 4-3 margin) recognized it as interstate commerce with the South Eastern Underwriters Association (SEUA) decision.

In response, the Congress passed the McCarran-Ferguson Act that suspended specified federal antitrust laws until 1948. McCarran-Ferguson allowed the states to continue to regulate insurance, even though it was interstate commerce, and provided limited anti-trust protection to

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2 The list of "others" includes the federal Occupational Safety and Health Administration (OSHA) for occupational injuries; fire marshals for fire losses; state motor vehicle departments that receive VIN's and various evidences of insurance; the federal Highway Loss Data Institute (HILDI) for auto losses, various fraud bureaus, etc.

cooperative activities between insurers to the extent that these activities were regulated by the states. It was argued that pooling was necessary to provide credible ratemaking data. Rating bureaus (certainly in their form at that time) could continue to exist only if the states passed laws to regulate them. The following year, the NAIC adopted industry-supported model laws that were subsequently passed in almost all of the states.

It is important to remember that the 1945 NAIC model laws predated electronic data processing equipment. They were drafted when statistical compilation was a tedious manual activity (instead of a tedious electronic activity). A careful study of the data collection provisions in these laws is necessary to understand what state statistical activities are ostensibly designed to do. The laws in most states follow these old NAIC models and read (in part) something like the following:

> The commissioner (may or shall)[3] promulgate reasonable rules and statistical plans[4], which may be modified from time to time and which shall be used thereafter by each insurer, in order that the experience of all insurers may be made available at least annually in such form and detail[5] as may be necessary to aid in determining whether *rating systems comply with the standards set forth in section [ ]. The commissioner may*[6] designate one or more advisory organizations or other agencies to assist in gathering such experience and making compilations thereof.

While some states allow data to be reported directly to them, other states do not accept direct reporting and virtually all insurers choose to satisfy their statistical data reporting requirements through statistical agents, even where they could report directly to the state. The ease of reporting to a single source is a major consideration for multi-state insurers, as is the technical support provided by statistical agents. Another consideration is that reporting data through a statistical agent generally avoids the state being in possession of detailed statistical data for the individual insurer. Data in the possession of the state is clearly subject to Freedom of Information Act (FOIA) requests, but data possessed by statistical agents has generally managed to stay beyond the grasp of such requests. (This concern will be discussed further in the FOIA section of this paper.)

Some statistical agents have existed only to collect data for statutory purposes, while others collect data for advisory organizations. In fact, advisory organizations generally do not have separate licenses as statistical agents, as licensure as an advisory organization customarily

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3 The NAIC model law was changed from "shall" to "may" in the early 1990's. Some states have "may," but "shall" is still most common.

4 As most readers know, statistical plans are large, complex sets of documentation that require a considerable amount of time for persons with specialized experience to write. With few exceptions, state insurance departments do not have staff with the time or background necessary to write statistical plans. However, it is not beyond the ability of states to specify the data elements to be collected or to instruct national statistical agents of state exceptions necessary to obtain the data necessary to fulfill the needs of a specific state.

5 This is a strong statement. The standards referenced are that each rate on file (whether filed by an advisory organization or an individual insurer) shall not be "excessive, inadequate or unfairly discriminatory." This implies that statistical compilations should be down to the level of individual classification detail. While insurers generally report data with class detail to statistical agents, the reports that are subsequently provided to regulators often do not get down to this level of detail.

6 The "may" is noteworthy, because it leaves the door open to the regulator being the statistical agent. In practice, however, this only occurs rarely.

authorizes them to collect statistics. For most lines and states, the data reported to statistical agents for statutory purposes is only a subset of the more detailed data necessary for ratemaking that is collected by advisory organizations. Therefore, in addition to making loss costs, advisory organizations also use a subset of the data that they collect to satisfy insurers' statutory reporting requirements.

Most state insurance departments are trivial users of insurance statistical data in comparison to advisory organizations, both in terms of the actual amount of data that they handle as well as the nature of the analyses that they perform. In part, this has been because many of the analyses in which the states are interested are, in fact, the same analyses or summaries provided by advisory organizations, statistical agents and large insurers. There is little reason for states to replicate work that has already been performed elsewhere.

The statistical output provided by statistical agents and advisory organizations to most states for most lines has tended to be highly summarized industrywide aggregations. These statistical summaries supplement other sources of information (i.e., Annual Statement Page 15's, rate filings and market conduct exams) used by insurance departments as they attempt to assure compliance with state rating laws. In general, the availability of these highly summarized reports to regulators and hence to the public has failed to generate controversy or concern.

In the author's opinion, the data requested by and provided to state insurance departments can be expected to become more detailed as state insurance departments increasingly take advantage of the processing power of modern personal computers. Consider that the goal of statistical reporting laws is, "to assure that the experience of all insurers is made available at least annually in such form and detail as is necessary to aid in determining whether rating systems comply" with the rating law. Do highly summarized industrywide aggregations provide enough information to fulfill this charge?

Experience has shown that regulatory demands for data most commonly arise out of market problems. Consider the demand generated by market crises – medical professional liability in the 1970's, products and general liability in the mid-1980's and workers' compensation in the late 1980's and early 1990's.

Of course, controversies and the data demands that inevitably result are not entirely restricted to market crises. Controversies relating to urban insurance data arose even though personal lines insurance is almost always competitive. The important point is that regulatory demands for data customarily increase when there are market problems. Yet markets have been virtually crisis-free since PC's with enough power to handle large databases have become common and inexpensive (since about the early 1990's). It seems easy to imagine that state insurance departments, armed with PC's that can handle gigabytes of data, will seek significantly greater amounts of detailed data when the next crisis or controversy brews. Sooner or later, a larger number of insurance departments are likely to seek detailed insurer-specific data, either directly or through statistical agents and advisory organizations.

Trade Secrets

A trade secret is information that you have – and that others don't – that would be of potentially significant value to others, customarily one or more of your competitors. A detailed list of your customers would usually be valuable to your competitors. This is in contrast to an inventory listing of your furniture and office supplies. The inventory listing may be quite valuable to you, but its value would not be affected if a copy of it were leaked to one of your competitors. What benefit would they receive from it? What harm would it do to you?

The intent of trade secret law is to provide protection for certain types of information that would be of value to others. Absent legal recognition of its value, an insurer's employee could sell an information-packed list of insureds to a competitor and the insurer would probably have no legal recourse against either its devious employee or the competitor. The legal recognition provided by trade secret laws allows this recourse. In the case of misappropriation of trade secret information, trade secret law may allow both injunctive relief and damages. Criminal penalties may also apply to the perpetrators. (The complexities associated with possible legal remedies are beyond the scope of this paper. The point to be made is that they exist.)

Most states (about 40) have passed the Uniform Trade Secrets Act and the legal principles that apply under common law are very similar. The following definition is paraphrased from that act:

> A trade secret is information that derives independent economic value, actual or potential, from not being known to other persons who could obtain economic value from its disclosure or use. It must be the subject of efforts that are reasonable under the circumstances to maintain its secrecy and outside parties may not be able to ascertain it at a reasonable cost by proper means.

It follows that a court will almost certainly reject an assertion of trade secret status if <u>any one</u> of the following requirements is not met:

- <u>The information must be of substantial value to competitors (were they to have it).</u> For instance, competitors would probably find a detailed list of insureds to be of substantial value, while an inventory listing of furniture and office supplies would be of minimal value.

- <u>Reasonable efforts must be made to keep the information secret.</u> The amount of effort that is "reasonable under the circumstances" to maintain secrecy is not easily characterized, but insurance data managers should be cautioned that the mere expectation that no one will copy the information is unlikely to be enough.

- <u>The information must not be ascertainable to outside parties by proper means at a reasonable cost.</u> For instance, a complete data-rich listing of insureds showing premiums and coverage amounts is probably not available except from the insurer. But a listing of workers' compensation insureds and their expiration dates for a state may be available from the state workers' compensation commission, and this would eliminate the trade secret status for this type of information in such a state.

These elements often involve "questions of fact," meaning that the determination is not purely objective, but involves judgment by the courts. Adding to the uncertainty, there has not been a significant number of prior court cases that have directly involved most types of insurance data questions, with the exception of customer list questions. The major question to be settled with otherwise straightforward customer list situations is generally whether the list is significantly more valuable than lists that can be developed from at a reasonable cost from openly available information. For instance, lists of homeowners and the value of their real property can generally be found at county courthouses, sometimes even in an electronic format. The amount of insurance would be of additional value, although some may argue that. But if this information were to be coupled with expiration dates, liability limits, amounts of scheduled property and premiums for each coverage, then there would appear to be little doubt that this would be of considerably more value to competitors than simpler lists available from public documents.

Only a few lower court cases have addressed trade secret questions for insurance statistical data of the nature that is routinely reported to statistical agents and advisory organizations (and which can eventually end up in the hands of state insurance regulators). The most notable case is a 1997 lower court case in Missouri, *Ganey, et al., vs. Missouri Department of Insurance, et al.* A newspaper in St. Louis wanted copies of insurer-specific premiums and losses by postal ZIP code from the Missouri Department of Insurance. The court agreed with insurer assertions that the data was trade secret and also affirmed that Missouri's public record law protected trade secrets from disclosure. The court noted, however, that the Missouri Department of Insurance should not presume that trade secret data will always be trade secret, noting that the value of marketing data is likely to diminish over time. The Missouri Department has since promulgated a regulation providing that data more than three years old will be released. This regulation is being challenged at this writing. It is likely that more litigation will be necessary before a reliable pattern can be ascertained for the trade secret status of various types of insurance statistical data.

Trade secret concepts are particularly relevant to data managers in their dealings with such entities as managing general agents and other types of business partners. While these dealings and internal applications (for instance, data mining) have made insurers more aware of the value of the data in their possession, the primary reason that the trade secret topic is the topic of public discussion more now than it was 10 or 15 years ago relates to the importance of this concept for information in the possession of governmental entities.

Freedom of Information Act (FOIA) Considerations

Virtually all government entities have some form of law governing the disclosure and distribution of information in their possession. Although the Freedom of Information Act (FOIA) is a federal law, its concepts are copied by laws in each of the states and much of the case law used to answer disclosure questions under state laws comes from cases in federal courts where FOIA laws are being applied. The general principle of FOIA laws is that every piece of information in the possession of the government should be subject to disclosure unless there is some specific reason (e.g., national security) to keep it confidential. Government should be accountable to the governed, and it can be argued that the ability of consumers, academics and the press to access the information underlying government decisions will result in better government, even in the majority of situations where consumers, academics and the press never avail themselves of this opportunity.

A problem with FOIA laws is that they provide the same broad access to information for competitors and commercial users as they do for consumers, academics and the press. While there are many situations where it is a sensible and proper function of government to obtain information for the purpose of its beneficial dissemination, it would appear desirable – "good government," if you will – for these situations to be identified and acted upon directly, rather than being the haphazard by-product of FOIA laws.

It has been the author's insurance-related experience that consumers, academics and the press comprise only a tiny percentage of the total public records traffic. In a Midwestern insurance department where an ordinary day will have several people viewing public records, a consumer, press or academic person may show up once or twice a year. It will probably be a graduate student seeking background for a paper. As many of the commercially-affiliated visitors are repeat customers, there can be little doubt that their opinion is that they are able to obtain commercially valuable information about their competitors that could not be obtained elsewhere, at least not at such an affordable price.

While this is a problem with FOIA laws, the total amount of information disseminated in this fashion may still be too small to offset the goodwill that results simply because the public knows that these records are available should they ever want to see them. In addition, the widespread protection of information filed with insurance departments would be a hindrance to employees at these departments who, even though they do not routinely provide documents to the public, counsel and respond to members of the public based on the insights that they glean from this information. Were this information to be protected, this muzzling of department employees could routinely put them in awkward situations. It is interesting to note that many associated with state insurance departments view this dissemination of information as a valuable service that enhances competition.

Although the underlying reasons for their existence are similar, it should be noted that the details of FOIA laws vary significantly from state to state. Procedures vary, and "exemptions" (classes of information that do not need to be made public) are mandatory in some states and discretionary in others. Even the definition of what constitutes a public record varies from state to state. As such, the reader should be cautioned that this paper can only make generalizations and to check the specific laws of every state where they have serious FOIA-related questions.

Under FOIA laws, trade secrets are one class of information that either may or shall (depending on the state) be protected from disclosure. For that reason, trade secret concepts are important to insurers when their data is in the possession of a governmental entity. A related exemption under FOIA laws is for "commercial or financial information ... (that is) privileged and confidential." On its face, this language appears to be more sweeping than the courts have interpreted it. In practice, the courts have exempted confidential commercial or financial information if

(1) Disclosure would be likely to impair the government's ability to get information in the future, or
(2) Disclosure would cause substantial competitive harm to the entity that provided it.

In the author's opinion, the first prong of these exemptions appears likely to be applicable to many types of ad hoc special calls for insurance data. If a special call includes data that the regulator had not required to be collected, such that there was no assurance that it would be available, and if the insurers providing the data appear to have a choice whether or not to comply, then it would appear likely that this exemption could apply if a large number of the submitting insurers indicated that they would submit data only if an attempt was made to keep it confidential. A prior indication by the regulator that information would be viewed as confidential would also add strength to an argument of confidentiality, although one should be cautioned that such an indication may not withstand a challenge.

The first prong of these exemptions would be less likely to apply to reports from statistical agents using standard statistical data elements that the regulator had required to be routinely collected. The reason for this is that there is usually no question that the regulator can obtain such reports. The second prong might, but determinations of the likelihood to cause "substantial competitive harm" could be difficult, judgment-filled determinations similar to trade secret determinations of whether the information would be valuable to a competitor.

FOIA laws apply to insurance statistical data in the large majority of states[7], but this has not resulted in a significant amount of FOIA requests by third parties to obtain detailed statistical data. At least one obstacle to FOIA requests for detailed statistical data in most states has been that the states don't have physical possession of the data. Rather, it is in the hands of statistical agents and advisory organizations. With the well-publicized (in statistical circles, anyway) exception of Texas, the fact that the statistical data is in the possession of statistical agents and advisory organizations has apparently taken it out of the reach of FOIA requests. The Texas FOIA provides in part that:

> ... "public information" means information that is collected, assembled, or maintained under a law or ordinance or in connection with the transaction of official business:
> (1) by a governmental body; or
> (2) for a governmental body and the governmental body owns the information or has a right of access to it ...

If the FOIA's in all states included this language, then the barrier to FOIA access by third parties caused by having the data with statistical agents and advisory organizations would be smaller. The Texas language is relatively unique, however, and the language in most other states appears to make it more difficult for FOIA requests to successfully extend to data in the possession of a statistical agent or advisory organization.

If and when such requests are made – and the affected advisory organization or statistical agent will presumably oppose such requests – the courts will probably seek to determine the extent to which the requested information is genuinely a state record. The laws of the individual states and the facts that the courts will be given to consider may vary widely. If the regulator has never

[7] It is technically more accurate to say that FOIA laws apply to insurance statistical data in all states, but that they may be superceded by conflicting language that relates specifically to an individual type of state record. For instance, if the insurance code of a state specifically provides that a given type of record shall be held confidential, then it will be held confidential even though it might not otherwise qualify for a FOIA exemption. There are a few states with provisions in their insurance laws that specifically provide that certain types of insurance statistical data shall be held confidential. However, the author is unaware of any state with an insurance law that liberalizes a state's FOIA by specifically providing that some type of statistical data may or must be released.

adopted regulations requiring the collection of data, then the statistical agent or advisory organization would be in an excellent position to argue that its activities were entirely voluntary. It would be difficult for such data to be accessible through a FOIA request. The scales would begin to tip if a state had requirements that went so far as to specify the data elements that must be collected. Further state actions – like actual promulgation of statistical plans or other heavy involvement in the data collection process – would make it even more likely that the records in question would be treated for purposes of a FOIA request as if they were in the physical possession of the regulator.

There is yet another wrinkle here. While the considerations just described relate to whether statistical data in the possession of a statistical agent is a "public record," the simple fact that something is a public record doesn't mean that the public can get a copy of it. It may be exempt as a trade secret or as confidential commercial information. In addition, FOIA laws generally do not require the creation of reports to respond to public requests. In general, requests under FOIA laws must be for reports that are already in existence. The fact that a statistical agent or a government agency has the ability to create a report from its databases does not mean that it is compelled to do so. While databases in the possession of statistical agents have been set up so that various reports can be generated, they are customarily not in the form of reports. Therefore, while statistical agent databases may be potentially exposed to FOIA laws more than many suspect, other practical considerations appear likely to limit the amount of information that third parties could access through this mechanism

Please note that these views are speculative and that this is an especially difficult area in which to make a prediction of future developments. The author's best guess is that FOIA barriers to the access of data in the possession of third parties will slowly erode. However, lest one become too concerned over side-door FOIA access to information in the possession of a statistical agent, keep in mind that the main reason for that this topic has become so important in the last few years is the expectation that states will begin to ask for detailed electronic reports from the data which statistical agents have collected on their behalf. Once the state has physical possession of detailed reports, there can be no question that they will be subject to the provisions of the state FOIA (although FOIA provisions may still allow or mandate it being held confidential).

Several other details should be noted. Virtually any claim to an exemption from disclosure under a FOIA law will probably be lost if the information is submitted to a regulator without some form of explicit prior understanding or acknowledgment by the regulatory entity regarding confidentiality. Merely sending something to a regulator stamped "confidential" may have little meaning unless this follows a prior agreement or well-documented practice of the regulator.

Note also that the situations are rare where a regulator can agree with certainty to withhold information from disclosure. About all that a regulator can do in most situations is to agree to a good-faith attempt to respect a claim for confidentiality. Should a third party seek to obtain information that a regulator has agreed to keep confidential, the regulator's refusal to disclose the information can be appealed. A court can subsequently order the release of data that does not qualify for one of the FOIA exemptions, even if the regulator had agreed (erroneously, because he/she lacked the authority) to withhold it.

Controversies Surrounding the Disclosure of Insurer-Specific Statistical Data

Disclosure of insurer-specific statistical data by state insurance regulators has been the subject of debate over the past several years, both at the NAIC and at the state level, primarily in Texas and Missouri. (The situation in these states is unsettled as of this writing. In both states, the disputes involve insurer-specific personal lines data by ZIP code. In Missouri the disputed request was for premiums and losses by ZIP code, while the disputed request in Texas did not include losses. At this writing, the courts have barred disclosure in both states, but related disputes continue. A full discussion would be lengthy and quickly out of date.)

Although the debate at the NAIC has often been in terms of all types of P&C statistical data, the primary area of focus has also been insurer-specific personal lines data by ZIP code. In these debates, the position of the insurance industry has been unequivocally in opposition to public disclosure, whether for relatively complete data sets or for reports showing writings (but no losses) by insurer, by ZIP code. (Early in the history of these discussions, some viewed premium and exposure data as being less sensitive than loss data, but this distinction is rarely heard anymore.)

A primary and often-cited reason for trade secret protection is to protect the value of research. If valuable insights are dissipated soon after their discovery, then why should capital be invested to gain them? Insurers argue that the dissemination of their personal lines writings by ZIP code will reveal marketing insights that they have developed through years of research. Note, however, that the debates regarding the disclosure of statistical data have related to situations or requests where the data would be revealed for all licensed insurers. It is one thing for an insurer to assert that it would be harmed if some part of its data was revealed to its competitors, but it is different for an insurer to assert that it would be harmed if all insurers were forced to reveal the same data.

The fact that the industry is unanimous in its opposition to ZIP code data release leads some regulators to question the validity of these arguments. How can all insurers have insights that allow them to perform better than the market? It has proven difficult for some regulators to accept trade secret arguments when there is a lingering suspicion that insurer sensitivity is attributable to reluctance for their writings to be examined by consumer advocates.

Actuaries should attempt to decide the answer to this question for themselves. The NAIC debate is intended to address prospective data collection, usually by statistical agents, rather than after-the-fact special calls. Suppose that premiums, exposures and losses are available by ZIP code on an industry aggregate basis. Other sources of information – primarily competitors' rate filings with accompanying documentation – are also available. Using this information, actuaries seek to develop profitable rate indications on a territorial or ZIP code basis, and may also seek to advise their marketing departments where competitors' rates appear to be on the high or low side versus these indications. Suppose now that the opportunity is offered to know competitors' writings by ZIP code. How much difference will this information make in the work that has already been done? If one answers that it is likely to be of significant value, then this affirms assertions of trade secret status. If one answers that it may be of interest, but that it wouldn't be likely to make much difference, then this would agree with those that dispute the validity of trade secret claims.

It is somewhat easier to give a dispassionate consideration of the data disclosure debate when something other than personal lines data by ZIP code is considered. Another relevant proposal to this debate (in fact, about the only other relevant proposal that has been discussed at the NAIC) is to obtain and reveal by-insurer writings for various general liability sublines. For instance, a report might be given showing lawyers' professional liability writings for the top 5 or 10 such writers in the state. One of the reasons for this is that insureds and producers will be able to ascertain the leading markets, thus making it easier for them to find coverage for lines where there are relatively few markets. Of course, this will also have the effect of revealing lines and situations where there is little competition, which may have the effect of inviting additional competition. To be sure, an insurer that has cornered a market doesn't want its potential competitors to know about it. It also may not want regulators or the public to know about it. Whether this information therefore constitutes a trade secret is arguable (as serious competitors may be able to ascertain this information by other legitimate means), but there can be no doubt that a market leader would rather not have this information published.

These debates match the competing interests of consumers and the marketplace (that is, new competitors and those willing to invest in expansion) versus the interests of those with established market positions. As illustrated by the example in the preceding paragraph, however, there may be times that a state insurance department could seek to further the public interest by making a conscious effort to gather data for the purpose of disseminating it.

Data Disclosure in Rate Filings

A discussion of trade secrets and "confidential commercial information" would not be complete without a discussion of data provided in support of rate filings. Many of the same types of information that are so zealously guarded in statistical databases are provided with rate filings in much easier to understand and straightforward forms. It is often information of a nature that would be a trade secret if it were not subject to disclosure in a rate filing. This disclosure occurs because the exemptions under FOIA laws that would otherwise be applicable in most states are preempted by rate filing laws that specifically provide for rate filings and supporting documentation to be open to public inspection.

Not surprisingly, insurers have occasionally sought to protect parts of their rate filings and at least a few regulators have agreed. The author has heard of states that have agreed to treat parts of the justification for a rate filing as confidential, in spite of what their law says, but it should be cautioned that there is no assurance that such treatment will hold up should a third party appeal the denial of access. Another occasional practice is for the regulator to examine the justification for a rate filing in a face-to-face meeting and hand it back across the table when he or she is done. The advantage to this from a filer's point of view is that the regulator will no longer have the document to disclose at some later date. Of course, the regulator is likely to be criticized should this practice be discovered. At least in some states, laws address disposal of documents in the possession of the regulator, and handing a document back across the table would probably run afoul of laws designed to assure that documents are not disposed of prematurely.

On balance, in spite of these questionable exceptions, the documentation contained in rate filings continues to be open to the public. The author therefore finds it surprising that there has been so little NAIC debate with regard to the information provided in support of rate filings.

There has only been debate regarding two specific situations; namely, catastrophe modeling and credit scoring, but these debates have not resulted in proposals to revisit the provisions of the model rating laws that call for the supporting documentation with rate filings to be disclosed. Perhaps the first NAIC-related indication of a sensitivity to disclosure of rate and form filings was a recent change to SERFF (System for Electronic Rate and Form Filing)[8] rules to ensure that the NAIC could not capture filings made via SERFF for the purpose of marketing them to third parties (or for any other purpose). The industry sensitivity appeared to be strong enough that, without this change, industry support for the SERFF system would have diminished to such a degree that the project would have died.

"Ownership and Control" Issues

A reference that is commonly heard in public discussions is that of "ownership" and "control" of data. "Ownership" of information is a valid concept, but "control" is more relevant and applicable for insurer statistical data. As will be seen, definitive statements regarding the concept of "control" are easier to make where regulatory requirements don't exist that require data to be reported.

Presume for the moment that regulatory considerations do not exist. In this case, data can be used by whatever entity is legally able to create or obtain it. For insurance, this entity will customarily be an insurer, although others – insureds, agents, brokers and organized groups of insureds – could also capture similar, identical or related data. Presume also that the data has value to others. After all, if no one else wants it, then it is not intellectual property and it is not relevant to this paper.

One choice for an insurer with valuable data is to share it with no one. With especially valuable data (i.e., trade secrets), this is often the rational choice. But the fact that an insurer doesn't want data relating to it to be used by others has no restrictive power over another entity if it has been able to legally capture the same information. In most situations, however, the insurer will be the only one with valuable data relating to its insureds.

Suppose that an advisory organization offers to provide valuable services in exchange for the use of an insurer's data. For many lines and insurers, the products provided by advisory organizations are necessary and agreements for sharing of this nature are common. With this sharing, the advisory organization gains whatever ability to use the data that may be provided in the contract between the insurer and the advisory organization. Commonly, the allowed usage of this data will be to produce average loss cost indications. The usage will also include the production of reports to provide to regulators.

Suppose that advisory organization "A" is approached by a consultant or another advisory organization that offers compensation in return for being able to use data in the possession of

[8] SERFF is an NAIC-developed system that allows insurers and advisory organizations to make electronic rate and form filings. It also allows the states to process the filings electronically, correspond with regard to filers via e-mail and to store the filings electronically. As such, many expect (fear) that SERFF will make access to rate filing materials much easier than has traditionally been the situation with submissions made on paper.

advisory organization "A." Advisory organization "A" could share the data – but only to the extent that its reporting insurers have authorized it to do so. Were this to happen, it would offer another example of insurer control. In these examples, all of which presume no regulatory requirements, note that data usage by advisory organizations and statistical agents is only as broad or as narrow as that to which the insurer is willing to agree. In these situations, insurers truly "control" their data.

Back in the real world, regulators exist and most of them want data to be reported to statistical agents or advisory organizations so that they can get reports on insurance in their state. This reduces the control that an insurer has over the use of its data and, depending on the details of the situation, it may also reduce the value of the data. At the very least, insurers are forced to allow their data to be combined with the data of other insurers and provided to the regulator. However, unless otherwise required by the regulator (i.e., as with workers' compensation in most states), the insurer does not need to give the advisory organization or statistical agent permission to do anything with its data other than to provide reports to the regulator. (Whether an advisory organization is interested in providing statistical services for insurers that don't want their data used for ratemaking is generally a matter between the insurer and the advisory organization.)

This loss of control could affect the value of an insurer's data if the data reported or disclosed by the regulator was useful to advisory organizations or others that might otherwise pay to use it. If detailed data is reported to the regulator and then made publicly available, why would an advisory organization want to pay the insurer for data that it can get at no cost from the regulator? This has usually been a hypothetical point because the states have not had much to report or disclose that was not generally available from other sources, anyway. It is still subject to more discussion than action, but Florida's initiative (discussed later in this paper) is an example of the situation just described.

As will be explained in the next section, "ownership and control" questions also apply, although in a somewhat different fashion, to the data possessed by advisory organizations.

Intellectual Property Issues Relating to Advisory Organizations

Advisory organizations are custodians of the intellectual property of insurers, but most of the intellectual property issues relating to advisory organizations relate to intellectual property that they have generated themselves. Copyright considerations are much more important for advisory organizations than for insurers. Trade secret issues are no less important, but they tend to cover different subjects for advisory organizations. After all, advisory organizations are not in the business of selling insurance.

Copyright law covers an incredible range of subject matter. Virtually anything that is original and fixed in some sort of tangible medium is copyrightable. Even the requirement for originality is minimal – works are not required to be novel. Such items as insurance manuals and policies are copyrightable. Look to the bottom of any form or manual page developed by an advisory organization and note the © notice in small print. The major exception[9] to copyright protection that is relevant to advisory organizations and to insurance in general is the following:

> In no case does copyright protection of an original work of authorship extend to any idea, procedure, process, system, method of operation, concept, principle, or discovery, regardless of the form in which it is described, explained, illustrated, or embodied in such work.

This means that copyright law cannot protect a trade secret. Rather, copyright law protects the manner in which ideas are expressed, not the ideas themselves. For instance, HO-3 forms cover residential structures from all risks of physical loss except for certain difficult-to-insure perils like earthquake, war, flood, etc. That idea cannot be copyrighted, but it takes a considerable amount of work to put those basic concepts into a sound insurance contract. As such, the insurance contract can be copyrighted, even if the idea behind it cannot, which means that many insurers may offer different forms that provide virtually identical coverage.

Some intellectual property situations for advisory organizations don't fit neatly into either the copyright or trade secret area. Consider the work and expense necessary for an advisory organization to perform an annual loss cost review for a complex major line of insurance. First, there is the work to amass and sanitize the underlying data[10], then the programming necessary to produce the various details in formats suitable for actuarial analyses, then the analyses and finally the production of a filing. To be sure, the loss cost filing is valuable *intellectual property*, but how can it be protected? Trade secret protection doesn't work, because loss cost filings must be publicly disclosed when they are provided to regulators. Yes, an insurer can't photocopy and use loss cost filings without paying the advisory organization, but the underlying data and the judgments that are the filing's primary source of value are not protected by copyright law.

In part, this loss of intellectual property isn't as bad as it hypothetically could be, largely because insurers want to use standard manual pages and also because most insurers are good corporate citizens that realize the need to pay their fair share. Where this falls apart more easily is when the entities that wish to use filing information are not traditional insurers. They might not be insurers at all. Such entities may include group self-insurers, various types of consultants or even other firms wishing to provide statistical agent or advisory organization services.

What if an advisory organization is asked to sell (license, technically) a copy of one or more of its databases? This is a difficult "ownership and control" question that is no longer hypothetical. Presumably, other vendors (competing advisory organizations or consultants) with technical and actuarial expertise could produce competing products if only they had access to the necessary databases.

The apparent ability that advisory organizations have had to deny the use of their data to other advisory organizations represents an issue that the regulatory community has only recently begun to consider. Even if insurers are not opposed to the sharing of data with other advisory

[9] Another exception that may be important to some is the "fair use doctrine" that allows limited use of copyrighted material for research, education and journalism among other endeavors.

[10] To the extent that this data must be reported for regulatory purposes – anyway – then the expense to amass it could not be attributed to the development of a loss cost filing. In general, however, the data necessary to develop loss costs is more extensive than that required to produce regulatory reports.

organizations, why would an advisory organization with a large percentage of the data for a given market be willing to share data except perhaps at a prohibitive price? (That is not to say that advisory organizations faced with this question have demanded unreasonable compensation, but only to point out the existence of uneven bargaining positions between the parties.)

There is only a limited amount of data and the legal question that most regulators will need to answer is whether this impediment to competition between advisory organizations is an impediment to competition between insurers in the marketplace[11]. If it is – and that does not appear to be an easy determination – it will be a challenge to deal with the situation in an equitable fashion. What is fair compensation to be able to use a database representing 20% or 40% or 80% or 100% of a market? How does one fairly value the decades of experience that are embodied by the existing data collection institutions?

With this background, suppose that insurers would like to choose between several competing advisory organizations offering products based on the largest possible portion of the market or, in the case of workers' compensation, the entire market. Or suppose that multiple entities would like to provide these products. Obviously, only one entity can provide these products if only one entity has access to the data necessary to produce them. It is beyond the scope of this paper to decide whether multiple advisory organizations are in the public interest or whether current laws encourage or discourage them. Suffice it to say that there appears to be enough interest in the marketplace and from insurance regulators in some states that there will be pressure for it to happen.

To either allow or cause multiple advisory organizations to share data, it would appear that prices must be attached to the existing advisory organizations' databases. But how can "fair prices" be determined? As will be seen in the next section, the Florida workers' compensation initiative largely avoids this controversy by making the data available to all advisory organizations at no real cost. Extending the Florida example to others involves much greater difficulties, however, and that will be discussed following the discussion of the "Florida initiative."

The Florida Workers' Compensation Initiative

The Florida Department of Insurance recently allowed multiple statistical agents to collect workers' compensation data. This was a first for workers' compensation insurance, even though it reflects the status quo for most other P&C lines. What is notable, however, is that the Florida Department has structured this arrangement so that ratemaking data is pooled and then shared among competing advisory organizations.

[11] State insurance laws generally provide plenty of authority to deal with situations where the action of some entity could restrain trade or reduce competition for insurance. However, if the inability of an aspiring advisory organization is not found to reduce competition for insurance, then the insurance laws of at least some states may not provide any direct recourse. This is uncharted territory. McCarran-Ferguson only exempts insurance from federal antitrust laws to the extent that it is regulated by the states. While the states clearly regulate the rates or loss costs produced by advisory organizations (monopolistic or otherwise), it is not so clear if or how the laws in most states have provided the authority or the charge to regulate pricing for data sharing or advisory organization services. Although a few disputes have recently arisen, it may be too soon to predict what will happen in this area as additional disputes arise.

In Florida, insurers will now be able to fulfill their data reporting requirements for voluntary insurance by contracting with any one of several designated statistical agents. Historically, all insurers had to report to a single organization. Similarly, insurers will be able to purchase services from any licensed advisory organization for workers' compensation. Notable aspects of this arrangement include:

- Experience Rating – if an insurer that purchases advisory organization services from "A" wishes to provide coverage to an employer whose data is with unrelated statistical agent "B," then statistical agent "B" must provide advisory organization "A" with the data that it needs to promulgate the experience modifier.

- Transfer of Data – If an insurer begins reporting to statistical agent "B" after being a client of statistical agent "A," then statistical agent "A" must transfer detailed historical data for the insurer to statistical agent "B."

- Insurance Department Ownership of Statistical Plans and Edit Packages – The Florida Department doesn't own the statistical agents' actual computer code, but it owns the statistical plans and the specifications for edit packages used by the statistical agents.

- Ratemaking Data Filed with the Department – Advisory organizations will get the data necessary to file rates from aggregate reports filed with the Florida Department of Insurance. (While Florida intends that only one set of advisory organization rates will ultimately be approved, all advisory organizations will be allowed to make rate filings. But one must not assume that this will happen in other states if they chose to follow Florida's approach.)

The Florida approach is relatively unique. For their own purposes, insurance departments have generally not attempted to get data suitable for ratemaking[12]. In Florida, however, the Department is working to make sure that the statistical reports that it receives as public documents are suitable to develop workers' compensation rates. This is intended to provide all advisory organizations with the access to the industrywide data necessary to make rates.

This approach will make it difficult for statistical agents to use income from the sale of advisory organization products to offset the costs to collect and cleanse data. Rather, insurers reporting data will need to pay in full for the statistical agents' costs. In turn, advisory organizations will receive data "for free." To emphasize this point, there is no requirement in Florida that an advisory organization must also collect statistics. As such, the pricing of advisory organization products will not need (or be able) to cover data collection costs[13]. Advisory organizations will not need to reimburse insurers for any value of the data, and they will not need to cover the costs to collect and cleanse the data – those costs will be paid by the insurers that report the data.

12 Texas has taken actions in this area on a multi-line basis. Texas has contracted with a single statistical agent for each line of insurance to amass detailed data with the intention that insurers and consultants as well as the Texas Department of Insurance can use it. The mechanics and the thrust of the Texas system are different than in Florida, however. Detailed (but not insurer-specific) industrywide data is made available to insurers, but the Texas Department and not advisory organizations set "benchmark rates."

13 In fact, Florida's contracts with their statistical agents prohibit any penalties or incentives to insurers with respect to the choice of statistical agent or rating organization.

Extending the "Florida Approach" to Other Lines and States

It is too soon to predict the extent to which other states may attempt to apply the concepts behind the "Florida approach." In addition, extending the "Florida approach" to other lines of insurance could be much more difficult than merely extending it to other states. The relative strength of arguments that favor and oppose measures to increase data sharing through regulatory mechanisms are likely to differ greatly for various lines of insurance.

Extending the Florida approach to workers' compensation in other states: Criticisms of the Florida approach include increased difficulties for the state to assure data quality for multiple statistical agents and that multiple statistical agents may be inherently less efficient than a single statistical agent. There is also a fear that competitive pressures may favor laxity on the part of one or more statistical agents in an effort to get the business of insurers that would prefer a statistical agent that is not quite so fussy about data quality. On the other hand, a statistical system that allows an insurer to select and stay with the same statistical agent for all of its states may make data reporting easier for insurers and may promote data quality. It remains to be seen whether competition for advisory and statistical services will ultimately result in better values for the insurance consumer.

The author's major additional concern with the application of this concept for workers' compensation in states other than Florida is that there will be an unfair shifting of costs to insurers if group self-insurers are able to purchase advisory organization services but are not required to report data. This is not a problem in Florida because, unlike many states, it requires group self-insurers to report data in the same fashion as traditional insurers. But this will be a consideration if this arrangement is extended to other states where group self-insurers are not subject to data reporting requirements, because then there will be entities realizing the commercial value of insurer statistical data that will not need to support its costs.

Extending the Florida approach to other lines: There are a host of practical and legal obstacles involved with extending the Florida approach to other lines. It would be most feasible in the personal lines area where several states (North Carolina, Texas and Massachusetts) already have provisions to compile ratemaking data at a single source. The only hurdle in these states would be for the laws to be changed to allow for multiple advisory organizations to use this data to provide services for client insurers.

For commercial lines other than workers' compensation, the practical hurdles (getting all insurers to capture the same relatively extensive set of data elements using the same data definitions) would be daunting. Beyond that, however, lie some "economic" hurdles that could be even more difficult to address.

Florida-style data sharing "for free," if it could be applied successfully to commercial general liability[14], might result in the availability of information to the surplus lines and other alternative markets at lower prices than they would otherwise need to pay. This would subsidize these

[14] Actually, Texas has already embarked on an experiment of this nature, although the system is not mature for commercial lines. As only a single state, although a large one, Texas may not prove to be an accurate test. Turning a complex set of commercial lines data into usable rate or loss cost indications may simply prove to be too much work for it to be economical for individual insurers or an aspiring advisory organization to undertake for a single state.

markets with no apparent public purpose for such subsidization. The same problem would exist with workers' compensation if the state freely allowed group self-insurers to compete, but didn't require them to report data. But this problem wouldn't exist for personal lines and it also wouldn't exist for workers' compensation in states that require group self-insurers to report data.

Another problem with a Florida-style "free data" approach applied to other lines is that it would work most easily with a system that requires the same detailed level of reporting for the entire marketplace[15]. That does not appear to be problematic for workers' compensation, but it would be for most other lines of insurance.

The status quo, where advisory organizations can purchase the license to use insurer data, with its value established in that fashion, appears to have the advantage of promoting efficiency. Those insurers that can produce quality detailed data in an efficient fashion are better positioned to report it and receive the benefits from doing so. This may prove to be especially true for commercial lines (other than workers' compensation), where deregulation may make usable data even more valuable in years to come. The problem with unwarranted subsidization of surplus lines insurers or group self-insureds is also more easily addressed. All of these considerations make the status quo attractive – if it works!

There is another legal point that may prove to be of consequence for other states as they consider this approach. The Florida approach clearly involves planned regulatory dissemination of data to promote competition (at least at the advisory organization level). While virtually all states have laws that require or strongly encourage the regulator to analyze statistical data to assure that rates are not "excessive, inadequate or unfairly discriminatory," probably very few states have laws that provide authority for the state to obtain data with the specific intention of packaging it for distribution in order to promote competition. Even though the author expects that state laws will tend to grant broader authority in this area over the next few decades, it should be noted that many states currently do not have laws that authorize activity of this nature.

Speculation about the Future

The purpose of this paper has been to highlight intellectual property issues that will become more important to the insurance industry over the coming decade. It has become easier for virtually anyone to use large amounts of detailed data – if only they can get their hands on it. This will create more demands for data, which makes it appear certain that the value of relevant data will increase. This may become especially evident in commercial lines (other than workers' compensation) if commercial lines deregulation creates difficulties for those seeking to get sufficient amounts of relevant commercial lines data. The increased value of good commercial lines data will then become a business consideration even more so than it has been in the past.

These forces will lead to increased attention to FOIA laws, both by entities wanting to get data as well as from entities seeking to protect the value of what they have. The debate will be made

[15] A governmentally mandated system wouldn't necessarily need to treat everyone equally. Texas only requires its largest private passenger auto writers to report detailed data, while smaller insurers have lesser requirements. Other schemes could be devised as well, but the point to be made is that it would be much more difficult for a governmentally mandated system to be flexible on an individual insurer basis regarding the business that is reported in detail versus other reporting.

more difficult owing to controversies over consumer interests and a relatively high level of confusion regarding a complex topic area. The next ten years should be interesting to watch.

The Florida initiative is an example of the types of decisions that lawmakers and regulators may need to make over the next decade. In the future, regulators will need to address even tougher questions, as demands for data become more intense and the blurred distinctions between advisory organizations and consultants diminish even more. Should advisory organizations and statistical agents be required to share detailed data with each other? What about sharing ratemaking reports with all insurers? How can prices for this data sharing be determined? If some of these notions are desirable, then how can they be achieved equitably with no more government involvement than is necessary?

With all of these questions, the answers may be different for personal lines than for commercial lines and perhaps workers' compensation. The markets and public interest are quite different in these areas, and it is not unreasonable to expect that data-related regulatory decisions will be different as well.

The potential for ill-considered actions to result in a less-than-optimum flow of the information necessary to conduct the business of insurance is unsettling. Even if some of these speculations turn out to be wildly inaccurate, it appears almost certain that insurers and the regulatory community will face challenging questions for years to come. An understanding of intellectual property law as well as the philosophy underlying the law will be essential to making these decisions. The answers should reflect a reasonable harmony between public and private interests – the issues are clearly more than just a set of legal questions.

Parameterizing The California Workers Compensation Experience Rating Plan: Development of Primary and Excess Credibilities & Translation into B and W Rating Values

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PARAMETERIZING
THE CALIFORNIA WORKERS COMPENSATION EXPERIENCE RATING PLAN

DEVELOPMENT OF PRIMARY AND EXCESS CREDIBILITIES & TRANSLATION INTO B AND W RATING VALUES

WARD BROOKS

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Abstract

This paper documents the methodology used to develop the primary and excess credibilities which underlie the experience rating plan of the Workers' Compensation Insurance Rating Bureau of California (the Bureau) and the translation of these credibilities into the B and W rating values used in the experience rating formula. The method is demonstrated with an analysis based on projecting experience modifications for policy year 1991. This analysis was completed in 1998 as part of the Bureau's regular maintenance of the Experience Rating Plan. The basic approach is one of multivariate regression but with the use of ridge regression to address the multicollinearity between the primary and excess components. Empirical results are smoothed by fitting logistic cumulative density functions. A process of iterative parameter refinement based on an extension of the traditional quintiles test is used and the performance of each iteration is assessed based on a measure of plan efficiency.

1. INTRODUCTION

Preliminaries

We will begin with a brief review of the experience rating formula currently used in California. The formula is:

$$(1)\qquad \text{Modification} = \frac{Ap+B+W\cdot Ae+(1-W)\cdot Ee}{E+B} \quad \text{or} \quad \frac{Ap+B+W\cdot Ae+(1-W)\cdot Ee}{Ep+B+W\cdot Ee+(1-W)\cdot Ee}$$

where Ap	=	actual primary losses
Ae	=	the excess of a risk's actual losses over the actual primary losses
A	=	actual total losses (Ap + Ae)
Ep	=	expected primary losses based on the appropriate D Ratios
Ee	=	the excess of a risk's expected losses over expected primary losses
E	=	expected total losses (Ep + Ee)
B	=	a rating value relating to the credibility of primary losses
W	=	a rating value which relates the credibility of excess losses to the credibility of primary losses

The rating values, B and W, vary by size of risk as measured by Expected Total Loss, E.[1]

Actual Primary Losses, Ap, are determined by applying the following formula to each loss:

$$(2)\qquad \text{Primary Loss} = \frac{9{,}000\times \text{Actual Total Los}}{\text{Actual Total Loss}+7{,}000}$$

This formula is known colloquially as the "split formula." All losses less than or equal to $2,000 are wholly primary.

Though not immediately obvious, it can be shown that this modification formula defines implicitly primary and excess credibilities in terms of the rating values by the following relationships:

$$(3)\qquad \text{Primary Credibility, } Zp = \frac{E}{E+B}$$

$$(4)\qquad \text{Excess Credibility, } Ze = W \times Zp = \frac{W\times E}{E+B} \quad \text{Note that } W = \frac{Ze}{Zp}.$$

Where, primary credibility is the credibility attaching to primary losses (Ap); excess credibility, the credibility attaching to excess losses (Ae). Again, for the purposes of this analysis, we accept

[1]This paper presumes the reader is knowledgeable about workers compensation experience rating. The reader requiring additional background should consult the experience rating readings in the Casualty Actuarial Society's *Syllabus of Examinations*. In particular, see Gillam and Snader [1], Venter [2], and Gillam [3].

these credibility formulas as given. We do not consider whether other experience rating designs (such as a frequency-only plan, a frequency/severity split, or credibilities based on variables other than expected loss) might exist which are more accurate. Similarly, the split formula has not been reviewed to determine whether or not it is optimal.

Overview of the Methodology

Our goal is to determine, simultaneously, the primary and excess credibilities (Zp and Ze) appropriate for a risk of a given size. We will then translate our estimates of Zp and Ze into B and W rating values using Formulas 3 and 4. We cannot estimate Zp and Ze directly from the experience rating formula (Formula 1). However, after a little algebra, Formula 1 can be expressed as:

$$(5) \qquad \text{Modification} = 1 + Zp\,\frac{Ap-Ep}{E} + Ze\,\frac{Ae-Ee}{E}$$

where, to parameterize, we let Modification equal the *projection period empirical modification* or Actual Total Losses/Expected Total Losses for the projection period. Modification is the dependent variable in our model. The algebraic conversion of Formula 5 into Formula 1 is given in Appendix 1.

The actual and expected losses on the right hand side of the equation are for the *experience period*. We term [(Ap-Ep)/E] and [(Ae-Ee)/E] the *primary variable* and *excess variable*, respectively. The primary and excess variables are empirical values and are the independent variables in our model. Zp and Ze are the regression parameters to be estimated on these independent variables. As a practical matter, we will not estimate these parameters on an individual risk basis but rather by groupings, based on size and experience. Before continuing with the methods used to estimate Zp and Ze, we will discuss the construction of the database and the development of the groupings.

2. THE DATABASE

We will demonstrate the methodology by parameterizing the policy year 1991 at fifth report projection period. The experience period for policy year 1991 modifications is policy year 1987 at third report, 1988 at second report, and 1989 at first report, combined. For each risk, the following data was compiled:

<u>Experience Period (three policy years combined)</u>
Exposure (generally, reported subject payroll)
Expected Total Losses (based on Expected Loss Rates by class for the experience period)
Expected Primary Losses (based on empirical D Ratios, discussed below)
Expected Excess Losses (Expected Total Losses - Expected Primary Losses)
Actual Total Losses (subject to $175,000 per claim loss limit; $350,000 per catastrophe)

Actual Primary Losses (based on the split formula discussed above)
Actual Excess Losses (Actual Total Losses - Actual Primary Losses)

<u>Projection Period (one year)</u>
Exposure (generally, reported subject payroll)
Actual Total Losses (subject to $175,000 per claim loss limit; $350,000 per catastrophe)
Expected Total Losses (based on Expected Loss Rates by class for the projection period)

The empirical Expected Loss Rates (ELRs) are developed from the actual experience for the experience period (i.e., they are hindsight). Therefore, there is no systematic bias in the parameterization due to estimation error of the ELRs. Similarly, empirical D Ratios were determined using the policy year 1991 experience period data and the appropriate experience rating loss limit and death values. In practice, promulgated ELRs and D Ratios are estimated as all of the experience period data will not be collected until the experience modification for the last risk for a given projection period is issued. The empirical D Ratios tie to the actual experience and therefore parameter bias is again eliminated by benefit of hindsight. Because empirical ELRs and D Ratios are used, a risk's modification as calculated for this analysis is not necessarily the same as the modification actually promulgated for the policy year 1991 projection period. Appendix 2 provides the complete table of empirical ELRs and D Ratios for the policy year 1991 experience period. Appendix 3 provides a comparison of the empirical D Ratios in Appendix 2 with the D Ratios in the 1991 Experience Rating Manual for 39 "benchmark classes."

Partitioning of the Dataset and Grouping of Risks

There is a great deal of variation in the experience of individual risks. Later in this paper we will compare the performance of experience rating alternatives by looking at a measure of the proportionate reduction in total variance achieved by experience rating alternatives. To the uninitiated, the achieved reductions in variance which we will see, particularly for small risks, may seem surprisingly small. The variation explained by experience rating may be only about 1% for risks near the eligibility threshold. Yet this marginal improvement in pricing is just as important to the bottom line in insurance as the small marginal profit (typically less than 3%) of a grocery store's is to its bottom line. The variation explained for the largest risks is generally in excess of 15%.

But here we address the implications of individual risk variance to the organization of the data. Although attempts were made to avoid grouping risks, thereby retaining as much individual information as possible, there was too much variation in the individual risks' experience to obtain statistically reliable results using regression techniques.

This is not to say results could not be obtained--they were. But it was critical that we be able to statistically evaluate the results. For example, we needed reliable answers to questions such as: 'Does a shifted-logistic fit better than a regular logistic or some other curve?' and 'Is the bias in a plan, as measured by a weighted regression, statistically significant?' Because it is so large, the unexplained individual risk variation often overwhelmed the tests of statistical significance. To overcome this, risks were first partitioned into groups of similar size and then further sub-grouped based on their experience. Many partitioning and grouping schemes were explored with the mean results of each more or less the same. We decided on the following scheme which we found to be optimal for statistical significance.

First, all risks were sorted by experience period Expected Total Losses in descending order. The risk with the largest Expected Total Losses in the database is risk "number one." The risks were then partitioned into groups of 5,000. The five thousand largest risks made up group 1-5,000, or the "first group." Within each group of 5,000, risks were then sorted based on their experience period empirical modifications (experience period Actual Total Losses/Expected Total Losses) in ascending order. Claim-free risks, if any, would be among the first of each group of 5,000. When risks had the same experience period empirical modification (commonly for claim-free risks), they were sorted by experience period Expected Total Losses in descending order. Therefore, the first risk in a group of 5,000 where there was more than one risk with claim-free experience would be the largest risk with claim-free experience.

Within each group of 5,000, sorted as described above, the risks were divided into 100 sub-groups of 50 risks. The experience of each sub-group of 50 risks was combined (not averaged) to make one data record. Then, for each group of 5,000, ridge regression (discussed below) was performed on the 100 (5,000 / 50) data records.

The First Group--The Largest 5,000 Risks

The largest 5,000 risks form a more heterogeneous group in terms of size than any other group. For example, the average expected loss for the larger half of the first group, $1,633,606, is 4.2 times larger than for the smaller half, while the average expected loss for the larger half of the second group, $248,855, is 1.4 times larger than for its smaller half. Because of this, consideration was given to breaking up the largest 5,000 into five groups of a thousand. No significant improvements or meaningful differences in estimates resulted from this refinement. Further, breaking the first group into smaller groups would have necessitated the use of weighted regressions, complicating the analysis. Therefore, we chose to leave the largest risks in one group of 5,000.

We now return to directly estimating Zp and Ze, simultaneously, from Formula (5).

3. PARAMETERIZING THE PLAN

Multicollinearity and the Primary and Excess Variables

Unfortunately, we cannot apply straightforward multivariate regression because the primary and excess variables are highly correlated. This is not unexpected given the nature of the split formula. For example, for the first group of 5,000 the correlation between the primary and excess variables is 99.0% for the policy year 1991 experience period. For the sixth group, (risks 25,001 - 30,000) the correlation is 96.3%. This high degree of multicollinearity can result in unstable parameters of uncertain statistical reliability.

Is the multicollinearity present in the data severe enough to warrant an alternative estimation procedure? We will see later that it certainly is.

We explored several possible solutions to this problem and ultimately decided on ridge regression as the appropriate treatment. While ridge regression is commonly used in other disciplines, it is currently not covered in the Casualty Actuarial Society's *Syllabus of Examinations*, so many actuaries may be unfamiliar with it. Therefore, we provide here an introduction and, for the interested reader, further references. But first, we will briefly sketch the steps to follow so the reader will have context for the role of ridge regression in our overall methodology.

The ridge regression estimates are starting values in an iterative process. At each iteration we will refine *overall* credibilities using an extension of the traditional quintile tests used to evaluate experience rating plan performance and then refer back to the ridge regression results to determine appropriate *apportionments* between primary and excess credibilities. Each iteration will involve translating primary and excess credibilities into B and W rating values and recalculating modifications for each risk. This iterative process will continue until no further improvements in plan performance can be obtained by adjusting primary and excess credibilities.

Ridge Regression Overview

Ridge regression introduces a parameter, θ, into the least squares solution.[2] The vector of parameter estimates is given by the equation:

$$b_z(\theta) = (\mathbf{Z'Z} + \theta I_p)^{-1}\mathbf{Z'Y}$$

where $\mathbf{Z}$ is the vector of predictor variables, Ip is the identity matrix of dimension p, and $\mathbf{Y}$ is the vector of centered and scaled empirical modifications. When θ equals zero, the ridge regression estimates are the same as the usual least squares estimates. Exhibit 1 provides the ridge regression results for three select groups of 5,000 for the policy year 1991 projection year.

The ridge regression results, or ridge trace, on Exhibit 1 demonstrate that for ordinary least squares--that is, when θ equals zero--the estimates of primary credibility were generally greater than one, while the estimates of excess credibility were very small or even negative. For example, on Exhibit 1, multivariate regression for the fifth group gives Zp of 1.5959 and Ze of -0.0368. Clearly, these results violate our *a priori* constraints for the values of Zp and Ze--namely that Zp

[2]The following discussion of ridge regression summarizes the key points from our primary reference, Draper and Smith [4]. The reader may also find Miller and Wichern [5] and Johnson and Wichern [6] helpful.

and Ze are bounded by [0,1]. The ordinary least squares results shown in Exhibit 1 are typical for all sizes groups and partitioning schemes.

The introduction of a θ greater than zero in the equation for the parameter vector above can correct for the correlation between the variables, the cause of these unacceptable results. The parameters of the resulting equations are not least squares and are biased, but are more stable and, generally, of smaller mean square error. The stability and lower variance error should more than compensate for the bias introduced.[3]

Exhibit 2 provides a plot of each group's ridge trace, that is, a graph of θ, Zp and Ze from Exhibit 1. Determining the appropriate degree of correction--the appropriate θ--is key. As θ goes to infinity, the parameters will approach zero. The goal is to keep θ as small as possible to achieve the desired degree of correction. There are many approaches to selecting the optimal θ, which we will designate by θ^*. Draper and Smith [4] state that there is no mechanically best way to choose θ^*. We experimented with most of the methods discussed by Draper and Smith.[4] Ultimately, we developed our own method, the Maximum Excess method, which outperformed the other methods we tested.[5]

The Maximum Excess method begins by inspecting the ridge trace to locate that θ for which excess credibility is maximized, subject to the constraint that Zp and Ze are bounded by [0,1]. An examination of Exhibit 2 reveals that, for each group, there is a θ for which excess credibility is maximized. We term this θ our ***maximum excess*** *θ, θ_E*. We select the combination of primary and excess credibilities corresponding to θ_E for our initial credibility estimates. For example, on Exhibit 1, excess credibility is maximized when θ equals 0.27 for the fifth group. Therefore, θ_E = 0.27 and we select Zp = 0.7186 and Ze = 0.1273 as initial values for the fifth group. This process is repeated for each group. Exhibit 3 provides a summary of each group's Maximum Excess selections. The corresponding values promulgated in the 1997 Plan are also shown for comparison. Note that, because this is empirical data, the Maximum Excess credibilities are not monotonically decreasing across groups. The Fitted Credibilities on Exhibit 3 smooth out this empirical noise. We'll come back to the Fitted Credibilities shortly, but first, a few more comments on ridge regression.

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[3]Tests performed while developing the 1997 Plan parameters found that the methodology in this paper developed *overall* credibilities comparable to those obtained with the prior methodology which was last used to parameterize the 1984 Plan and which did not correct for multicollinearity. The prior methodology did not allow for direct estimation of primary and excess credibilities separately nor for the ability to directly translate these credibilities into B and W rating values.

[4]An overview of the most promising method discussed by Draper and Smith, Hoerl and Kennard's δ, is provided in Appendix 4.

[5]In prior analyses, the Maximum Excess method resulted in the best parameters, as indicated by our performance measures (discussed below), see Workers' Compensation Insurance Rating Bureau of California [7], [8], and [9]. A comparison of the relative performance of the Hoerl and Kennard's δ method with that of the Maximum Excess method is provided in the Agenda and Minutes of the July 2, 1996 Meeting of the Actuarial Committee of the Workers' Compensation Insurance Rating Bureau of California [8].

The ordinary least squares estimates of Zp and Ze routinely fall outside the [0,1] constraint thus demonstrating the need to address multicollinearity. We have selected ridge regression as the treatment. As to ridge regression's appropriateness, we note here that Draper and Smith [4] discuss two circumstances for which ridge regression is "absolutely" the correct way to proceed. The first is when we have "[a] Bayesian formulation of a regression problem with specific prior knowledge of a certain type on the parameters." The second is when we have "[a] formulation of a regression problem as one of least squares subject to a specific type of restriction on the parameters." The constraint on credibilities to be between zero and unity justify ridge regression in this situation. Indeed, it may be possible to further refine the ridge regression procedure to the *a priori* constraints (for example, the parameters could be constrained to the ellipse 0<=Ze<=Zp<=1).

Miller and Wichern [5] discuss several ways to deal with the problems of multicollinearity, including reselection of the independent variables, discarding independent variables, alternative estimation procedures and ridge regression. Clearly, discarding a variable is not an option here. A principal components treatment would be feasible but would require altering the familiar B and W structure of the rating plan as there would be no simple, direct linkage (i.e., Formulas 3 and 4) between primary and excess credibilities and the B and W rating values.

Smoothing the Primary and Excess Credibilities

The ridge regressions have given us a series of indicated primary and excess credibilities by size of risk. We test each iteration's credibilities by calculating experience modifications for every eligible risk. The Bureau's systems are designed to accommodate Formula (1), the traditional B and W formula. To accomplish this mass re-rating requires development of a B and W table for each iteration. To develop a B and W table we first smooth the selected credibilities by fitting them to a curve.

The series of credibilities corresponding to the selected θs is smoothed by fitting the primary series and excess series separately, to a logistic cumulative density function (CDF). The logistic CDF is given by

$$F(x) = \frac{1}{1+\exp[(\alpha-X)/\beta]}$$

where X = the natural logarithm of a group's median Expected Total Losses for the experience period. Excess credibilities were fit to a translated, or shifted, logistic CDF, where

$$F(x) = \frac{1}{1+\exp[(\alpha-X)/\beta]} - \text{Shift}$$

A statistically significant shift greater than zero implies that excess credibility approaches a limit less than one (specifically, unity minus the shift). The credibilities were fit by applying the nonlinear Levenberg-Marquardt algorithm to the indicated ridge regression Zp and Ze. Exhibit 4 shows the indicated and fitted values for the initial iteration. Finally, we note that, for the B and W table to have the usual properties of B descending and W ascending with increasing Expected Total Loss, the parameter β must be less than unity for primary credibility.

Developing B & W Rating Values from the Primary and Excess Credibilities

Exhibit 5 provides the formulas used to translate the fitted primary and excess credibility curves to B and W values. First, the fitted equations for Zp and Ze are shown. We then make use of the fact that W = Ze/Zp. Using some straightforward (though unattractive) algebra, we can express W in terms of the natural logarithm of the experience period Expected Total Losses, E. With this closed form expression for W, we can determine the Expected Total Losses corresponding to any given W. (Theoretically, we could do this by inverting the equation; practically, we do this using Lotus 1-2-3's Backsolver or a bi-section algorithm.)

We construct the Table of B and W values (Exhibit 6) by first determining the Total Expected Loss ranges for each W in increments of 0.01. For example, to determine the Expected Loss range corresponding to W = 0.25, we determine (using Exhibit 5, Formula 3 and Lotus 1-2-3's Backsolver) the expected losses corresponding to W = 0.245 and W = 0.255. Next, we determine the Total Expected Losses corresponding to the midpoint of each range by averaging the endpoints ($215,673 for W = 0.25). For the midpoint Total Expected Losses we determine Zp (Exhibit 5, Formula 1). Finally, we use Formula 4 of Exhibit 5, which is a closed form expression for B in terms of E and Zp, to determine B for the midpoint of each Expected Loss Range.

Iterative Parameter Refinement

A number of tests were used to assess the performance of each set of credibilities. Each test was performed for all risks and for five groups of risks based on size (Expected Loss Quintiles).

Quintile tests were examined to assess the overall performance of parameters. A quintiles test first ranks risks by their experience modifications, then divides the population into five groups (quintiles), and then compares their relative standard and manual loss ratios. Each modification quintile has approximately 20,000 risks. Quintiles tests are a commonly accepted actuarial technique for evaluating the performance of experience rating plans [2]. The quintiles tests are shown in Exhibit 7. Ideally, we expect the standard loss ratios (the loss ratios using the modified premiums) for all groups to be the same. If a group's standard loss ratio is markedly higher or lower than the others, this indicates that the general credibility for the group is too low or too high. In particular, there should be no marked trend in the standard loss ratios and we would like the variance of the standard loss ratios to be small. Conversely, we expect the manual loss ratios to be positively correlated with the experience modifications. This indicates the experience modification does a good job of differentiating risks based on their expected future experience. If the plan did not do this, the manual loss ratios would tend to be the same.

We developed an extension of the quintiles test in which we regress the standard loss ratio against the experience modification. Exhibit 8 shows the standard loss ratios and number of risks by intervals of the projected experience modification for five groups based on size and for all risks combined. Again, absent noisy data, a perfect plan would produce the same loss ratio after modification for all risks. To determine what adjustments, if any, might be necessary, we look for patterns in the standard loss ratios across modification interval for risks of approximately the same size (a given Expected Loss Quintile). We quantify the pattern by performing a weighted regression. Generally, the pattern, if any, is a simple trend and we fit this with a straight line. The coefficient on the independent variable (projection modification) quantifies how much credibility should be increased or decreased. If all risks' standard loss ratios are the same, the coefficient will not be significantly different (statistically) from zero and no adjustment is indicated. If standard loss ratios are positively correlated with the proposed modifications, then credibilities are too low. If standard loss ratios are negatively correlated with the proposed modifications, then credibilities are too high. (The logic behind this adjustment is presented in Appendix 5.) The R-squared for the regression as a whole relates to the amount of variation explained and generally is expected to be small for experience rating. The statistical significance of the coefficient on the independent variable, the indicated adjustment, generally is significant at a 5% or 10% confidence level. When this coefficient is statistically insignificant, we exercise judgment in making an adjustment. The results of these regressions are provided in Exhibit 9.

The quintile test weighted regressions indicate that the appropriate adjustments to credibility vary by size. For example, from Exhibit 9 we see that the indicated adjustment for the largest risks is 0.04859 while for the smallest risks it is 0.3835. To account for this variation by size, the indicated adjustments (the coefficients on the independent variable) for each size quintile are fit to the quintiles' median risk ranks to determine a smooth transition in adjustment by size (Exhibit 10). When the pattern of adjustments is not smooth across size quintiles, linear interpolation from quintile to quintile may be used. Exhibit 11 provides a plot of the bias adjustments for the initial and subsequent iterations. As our estimates are refined, we expect the line graphed on Exhibit 11 to fall toward the x-axis with successive iterations, assuming the bias coefficients maintain their statistical significance.

From this fit of indicated adjustments to size of risk, an adjustment appropriate to each group of 5,000 can be calculated. The indicated adjustment for each group is then applied to the *overall* credibility underlying the prior iteration to determine the Overall Credibility After Adjustment (Exhibit 12).

Our new overall credibilities for the next iteration must now be split into primary and excess components. The problem for successive iterations is how to select primary and excess credibilities which are not highly multicollinear. To clarify our chosen solution to this problem, let us first consider a theoretically more idealistic solution. We propose that for each group, some combination of Zp and Ze on the ridge trace is optimal in terms of optimizing a given performance measure as well as correcting for multicollinearity. Specifically, given any performance measure, we could determine each group's optimal θ by developing a B and W table for each valid Zp/Ze combination on the ridge trace (i.e., for each θ for which Zp and Ze are bounded by [0,1]), calculate the corresponding performance measure and select the optimal combination. These results could then be smoothed out across risk sizes as discussed above.

Such a method, while theoretically appealing, is currently too computationally intensive. The Maximum Excess method, logistic smoothing, and quintile adjustments serve to get us reasonably close. Because the goal is more optimal positioning on the ridge trace for each group--not proportionate adjustment--we return to the ridge trace to find Zp and Ze combinations for which the overall credibility is closest to the new indicated credibility.

An example will clarify our procedure. For the fifth group, the overall fitted credibility before adjustment was 0.2931 (Exhibit 12). The indicated adjustment for this group from Exhibit 10 is to increase credibility 12.76%. So the desired overall credibility after adjustment is 0.3306. Returning to the ridge trace for this group, Exhibit 1, we find the Zp and Ze which provide overall credibility closest to 0.3306 at $\theta = 0.11$. Our credibility selections for the fifth group to start the first iteration become Zp = 0.8662 and Ze = 0.1155. (The initial Maximum Excess values were Iteration 0.) This procedure is followed for each group. For each iteration credibilities are then logistically smoothed before preparing the B and W table.[6]

The above process is repeated iteratively until a set of credibilities is developed for which the overall performance of the plan was maximized and no further adjustments to credibility were indicated. Generally, we determine this point by going too far. That is, adjusting until the performance deteriorates and then selecting the prior iteration.

4. EVALUATING THE PARAMETERIZATION

The Performance Measure

The selected performance measure is the efficiency of each iteration; that is, the proportionate reduction in total variance. This measure was developed by Meyers [10]. We have calculated each tested plan's efficiency on both a manual premium-weighted and risk-weighted basis and by size quintile and for all risks combined. The manual-premium basis attaches weights so as to minimize error in terms of absolute dollars. The risk-weighted basis implies the accuracy of a small 10-employee risk is of the same importance in parameter development as a large 10,000-employee risk. While generally not true, there is concern that the risks who must live with their experience modifications without recourse are smaller risks. Large risks are more likely to receive special scrutiny and have options largely unavailable to small risks, such as retrospective rating, large deductible plans, or schedule rating. Therefore, when looking at the all risks

[6]Other approaches were considered but dismissed. For example, a straightforward approach might be to increase both Zp and Ze by the indicated adjustment, allowing for special handling when the indicated primary credibility would be in excess of unity. This approach was tried in the early stages of our research but the results proved unsatisfactory and incongruous with the multicollinearity correction we sought through ridge regression. Another approach we considered was to maintain the relativity between primary and excess credibilities implied by the Maximum Excess selections. This approach's results also proved inferior.

combined efficiency, we look at both bases to ensure the best plan is not one which serves only one class of risks.

Exhibit 13 summarizes the efficiencies of each iteration. The credibilities underlying the second iteration were selected as final since no further improvements in the all risks, manual premium-weighted efficiency were achieved after this iteration. For reference, risk-weighted efficiencies are shown for the promulgated 1997 Plan and a frequency-only plan developed in 1995.[7] The promulgated 1997 Plan's credibilities were based on parameterizing the policy year 1989 projection period as well as looking at other projection periods. The frequency-only plan was developed in 1996 as an alternative to the existing experience rating formula. In the end, the frequency-only plan was not adopted. However, the efficiencies for the frequency-only plan suggest that most of the information from the current experience rating formula comes from frequency.

We note that great care must be made in comparing efficiencies across projection periods. Experience rating works best when the same dynamics extend from the experience period through the projection period. Some periods in time are more or less stable than others. In California, in particular, highly aberrant and extreme experience was observed for policy years 1989 through 1991. Generally, the Bureau tries to avoid using these years in studies such as this, but tradeoffs must be made between the availability and age of data.

We also note that our experience in California suggests parameterizing an experience rating plan is less sensitive to the maturity of the data than might be first thought.[8] This is probably true for several reasons. First, under the current formulation, frequency accounts for most of the variation explained by experience rating. Second, the severity of individual claims is limited. So, using loss limitations effective for policy year 1998 ratings, of a claim which develops from \$50,000 to \$500,000, only an additional \$125,000 would be allowed in the experience rating. And finally, of the incremental dollars which would enter the experience rating, virtually all would be excess and subject to excess credibilities (around 33% for the largest risks and less than 10% for most risks). Indeed, the proportion of losses which are primary has grown substantially since the current split formula was last updated in 1985 (Appendix 6). The \$175,000 loss limitation has also been in effect since 1985.

Impact Tests

Finally, we examine the distribution of risks by current vs. indicated modifications, separately by Expected Loss Quintile and for all risks combined. This information, for the second and final iteration, is shown in Exhibit 14, and provides an overview of the number of risks which will be impacted in any given direction and the magnitude of the impact. The shaded diagonal on Exhibit 14 marks those risks with no appreciable change in modification. The further a risk is away from

[7]Manual premium-weighted efficiencies were not available.

[8]The reader might note that the policy year 1989 parameterizations were to third report level data while the policy year 1991 parameterizations are to fifth report level data.

the diagonal, the larger the impact of the revision in credibilities. Risks above the diagonal would see their modifications go down. Risks below the diagonal would see their modifications go up.[9] While the information presented in Exhibit 14 is in 0.10 increments, the Bureau reviews the impact tests in 0.01 increments in making its final evaluation. This information, in light of this analysis and findings in prior analyses, is used in any decisions to deviate from the indicated credibilities.

Exhibit 15 provides a comparison of indicated and promulgated credibilities for the 1997 Plan and the indicated credibilities for the policy year 1991 parameterization.[10] Exhibit 16 is a graphical presentation of the information on Exhibit 15. Exhibit 17 provides a comparison of indicated and promulgated B and W values for the 1997 Plan and the indicated B and W values for the policy year 1991 parameterization. Exhibit 18 is the graphical companion to Exhibit 17.

5. DISCUSSION AND CONCLUSION

In 1998, the Bureau's Actuarial Committee reviewed the analysis presented above and decided to make no changes to credibilities at that time. Instead, the Bureau's Actuarial and Governing Committees directed further research which will follow from the following discussion. The procedures demonstrated, however, are the same as those used to develop the credibilities underlying the experience rating plan current as of this writing (namely, for policies effective in 1997 through 1999).

The credibilities developed for policy year 1991 are quite different from those developed for policy year 1989 and earlier periods. In particular, primary credibilities are much higher across all risk sizes while excess credibilities are somewhat lower (Exhibit 17). We noted earlier that the proportion of loss dollars which are primary has grown considerably since the split formula was last updated (Appendix 6). We expect this explains much of this shift in credibilities. This shift was probably evident in 1989, but that was a period characterized by many small stress claims from plant closings and fraudulent claims from 'medical mills,' for example, which masked the shift at that time. The evidence argued for a review of the split formula and it was decided this would be done before revising the Plan credibilities.

The split formula can be thought of as one point in a spectrum between a frequency-only plan, where primary losses are limited to one dollar and all excess credibilities are zero, and self-rating,

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[9]Because revising credibilities will likely change a plan's off-balance, risks with no change to their modification may actually see a modest change in standard premium. Similarly, risks with modest changes in modification may even see their standard premium change the slightly in the opposite direction.

[10]The credibilities indicated for the 1997 California Experience Rating Plan were not adopted for all sizes of risks. The Bureau's Actuarial Committee elected to phase-in indicated credibilities for smaller risks. This was accomplished by allowing no change for the smallest risks for which B and W values were published and allowing the full change for risks with experience period expected losses of $20,000 or greater. To prevent a misleading comparison between the 1997 Plan and projection year 1991, Exhibits 15 through 18 show both the indicated and promulgated values for the 1997 Plan.

where full credibility attaches to both frequency and severity.[11] We noted that frequency-only alternatives have been developed which explain nearly as much variation as the current plan. This suggests a frequency/severity split might offer even greater performance. For our future research we propose to first isolate the predictive content of frequency experience and then to examine the predictive power of layers of severity. Such an approach might obviate the need to address multicollinearity.

We continue to work on other avenues to improve our methodology. For the quintiles test extension and bias adjustments of Exhibits 9 and 10, we are exploring refinement of the adjustments to the group-of-5,000 level, perhaps even adjusting each group independently to its optimal credibilities then smoothing across size of risk.

As with any project of this scale, of course, honing our methodology will always be a work in progress. To date, we have had neither the time nor resources to explore all the paths which might lead to further improvement. Nevertheless, this latest methodology has proved very satisfactory since its development and has offered new insights into the dynamics of experience rating.

[11]It happens that the frequency-only alternative we developed treated types of claims differently. Specifically, temporary and other indemnity claims were treated separately and medical-only frequency was not used at all. This does not detract from the proposed spectrum, but it does increase its complexity.

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[7] Workers' Compensation Insurance Rating Bureau of California, "Agenda and Minutes of the Actuarial Committee Meeting Held on May 30, 1996 in the San Francisco Office of the Bureau."

[8] Workers' Compensation Insurance Rating Bureau of California, "Agenda and Minutes of the Actuarial Committee Meeting Held on July 2, 1996 in the San Francisco Office of the Bureau."

[9] Workers' Compensation Insurance Rating Bureau of California, "January 1, 1997 Pure Premium Rate Filing."

[10] Meyers, G., "An Analysis of Experience Rating," PCAS LXXII, 1985, p287.

CALIFORNIA EXPERIENCE RATING PLAN **Exhibit 1**
RIDGE REGRESSION RESULTS
Projection Year 1991 5th Report

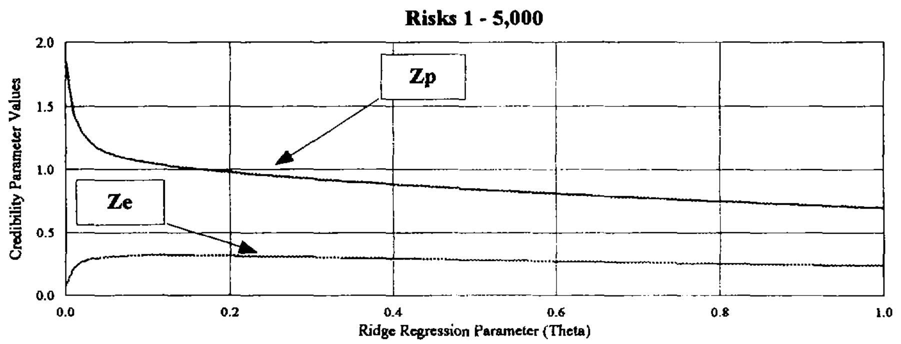
θ	Risks 1 - 5,000 (1st Group)			Risks 20,001 - 25,000 (5th Group)			Risks 45,001 - 50,000 (10th Group)		
	Zp	Ze	Overall	Zp	Ze	Overall	Zp	Ze	Overall
0.00	1.8494	0.0790	0.6388	1.5959	-0.0368	0.4330	1.1171	-0.0131	0.3079
0.01	1.4293	0.2210	0.6030	1.3700	0.0142	0.4043	1.0467	0.0009	0.2979
0.02	1.2901	0.2657	0.5896	1.2340	0.0442	0.3865	0.9902	0.0119	0.2898
0.03	1.2188	0.2869	0.5815	1.1426	0.0638	0.3742	0.9439	0.0207	0.2829
0.04	1.1743	0.2988	0.5756	1.0765	0.0776	0.3650	0.9050	0.0279	0.2770
0.05	1.1431	0.3062	0.5708	1.0263	0.0877	0.3577	0.8719	0.0339	0.2719
0.06	1.1195	0.3109	0.5666	0.9865	0.0953	0.3517	0.8432	0.0390	0.2674
0.07	1.1006	0.3141	0.5628	0.9540	0.1013	0.3466	0.8181	0.0433	0.2634
0.08	1.0849	0.3162	0.5592	0.9269	0.1060	0.3422	0.7959	0.0469	0.2597
0.09	1.0714	0.3175	0.5559	0.9038	0.1099	0.3383	0.7761	0.0501	0.2563
0.10	1.0596	0.3183	0.5527	0.8838	0.1130	0.3348	0.7583	0.0529	0.2532
0.11	1.0489	0.3187	0.5496	0.8662	0.1155	0.3315	0.7421	0.0553	0.2504
0.12	1.0393	0.3188	0.5466	0.8506	0.1177	0.3285	0.7273	0.0574	0.2477
0.13	1.0304	0.3187	0.5437	0.8365	0.1194	0.3258	0.7138	0.0593	0.2452
0.14	1.0221	0.3184	0.5409	0.8237	0.1209	0.3231	0.7013	0.0610	0.2428
0.15	1.0143	0.3180	0.5381	0.8121	0.1222	0.3207	0.6897	0.0624	0.2406
0.16	1.0070	0.3174	0.5354	0.8014	0.1232	0.3183	0.6789	0.0637	0.2385
0.17	**1.0000**	**0.3167**	**0.5328**	0.7914	0.1241	0.3161	0.6689	0.0649	0.2365
0.18	0.9933	0.3160	0.5302	0.7822	0.1248	0.3139	0.6594	0.0659	0.2345
0.19	0.9869	0.3152	0.5276	0.7735	0.1254	0.3119	0.6505	0.0669	0.2327
0.20	0.9807	0.3143	0.5250	0.7653	0.1259	0.3099	0.6421	0.0677	0.2309
0.21	0.9747	0.3134	0.5225	0.7576	0.1263	0.3079	0.6342	0.0685	0.2291
0.22	0.9690	0.3125	0.5201	0.7504	0.1266	0.3061	0.6266	0.0691	0.2275
0.23	0.9633	0.3115	0.5176	0.7434	0.1268	0.3042	0.6194	0.0697	0.2259
0.24	0.9579	0.3105	0.5152	0.7368	0.1270	0.3025	0.6126	0.0703	0.2243
0.25	0.9525	0.3095	0.5128	0.7305	0.1271	0.3007	0.6061	0.0707	0.2228
0.26	0.9473	0.3085	0.5105	0.7245	0.1272	0.2991	0.5998	0.0712	0.2213
0.27	0.9422	0.3074	0.5081	**0.7186**	**0.1273**	**0.2974**	0.5938	0.0715	0.2199
0.28	0.9373	0.3063	0.5058	0.7130	0.1272	0.2958	0.5881	0.0719	0.2185
0.29	0.9324	0.3053	0.5036	0.7076	0.1272	0.2942	0.5825	0.0722	0.2171
0.30	0.9276	0.3042	0.5013	0.7024	0.1271	0.2927	0.5772	0.0724	0.2158
0.31	0.9229	0.3031	0.4991	0.6974	0.1270	0.2911	0.5720	0.0727	0.2145
0.32	0.9183	0.3020	0.4969	0.6925	0.1269	0.2896	0.5670	0.0729	0.2132
0.33	0.9137	0.3009	0.4947	0.6878	0.1268	0.2882	0.5622	0.0730	0.2120
0.34	0.9092	0.2998	0.4925	0.6831	0.1266	0.2867	0.5575	0.0732	0.2108
0.35	0.9048	0.2987	0.4904	0.6787	0.1264	0.2853	0.5530	0.0733	0.2096
0.36	0.9005	0.2976	0.4882	0.6743	0.1262	0.2839	0.5486	0.0734	0.2084
0.37	0.8962	0.2965	0.4861	0.6700	0.1260	0.2825	0.5444	0.0735	0.2072
0.38	0.8920	0.2954	0.4840	0.6659	0.1258	0.2812	0.5402	0.0735	0.2061
0.39	0.8878	0.2943	0.4820	0.6618	0.1255	0.2798	0.5362	0.0736	0.2050
0.40	0.8837	0.2932	0.4799	0.6579	0.1253	0.2785	0.5323	0.0736	0.2039
0.41	0.8797	0.2921	0.4779	0.6540	0.1250	0.2772	0.5284	0.0736	0.2028
0.42	0.8757	0.2910	0.4759	0.6502	0.1247	0.2759	**0.5247**	**0.0736**	**0.2018**
0.43	0.8717	0.2899	0.4739	0.6465	0.1244	0.2746	0.5211	0.0736	0.2007
0.44	0.8678	0.2889	0.4719	0.6428	0.1241	0.2734	0.5175	0.0736	0.1997
0.45	0.8640	0.2878	0.4700	0.6392	0.1238	0.2721	0.5140	0.0736	0.1987
0.46	0.8601	0.2867	0.4680	0.6357	0.1235	0.2709	0.5106	0.0735	0.1977
0.47	0.8564	0.2856	0.4661	0.6323	0.1232	0.2697	0.5073	0.0735	0.1967
0.48	0.8526	0.2846	0.4642	0.6289	0.1229	0.2685	0.5041	0.0734	0.1957
0.49	0.8489	0.2835	0.4623	0.6256	0.1226	0.2673	0.5009	0.0734	0.1948

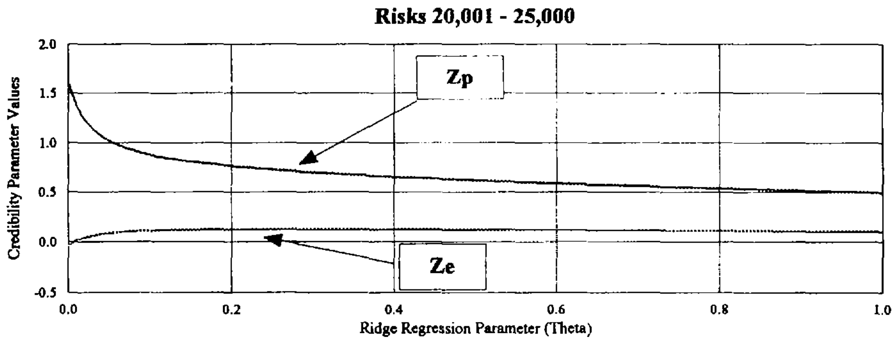
Notes: Overall Crediblity = (D x Zp) + ((1 - D) x Ze), where D is the empirical D-ratio for the group.
Valid combinations of Zp and Ze are those for which Zp and Ze are bounded by [0,1].

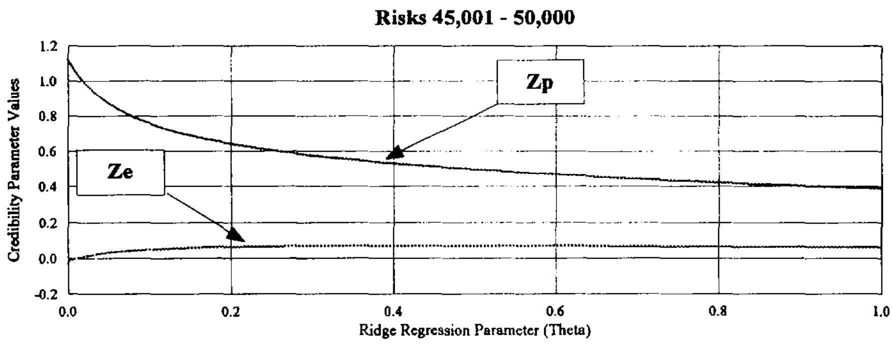
CALIFORNIA EXPERIENCE RATING PLAN

Exhibit 2

RIDGE REGRESSION RESULTS
Projection Year 1991 5th Report







CALIFORNIA EXPERIENCE RATING PLAN
MAXIMUM EXCESS RIDGE REGRESSION CREDIBILITIES
Projection Year 1991 at 5th Report - Iteration 0

Exhibit 3

Risks	Median Exper. Period Expected Loss	1997 Experience Rating Plan		Exp Period Empirical D Ratio	Maximum Excess Ridge Regression Values*				Fitted Values		
		Zp	Ze		θ	Zp	Ze	Overall	Zp	Ze	
1 - 5k	520,196	0.98381	0.37463	0.31619	0.17	0.99999	0.31674	0.53277	0.95084	0.32174	
5k - 10k	209,397	0.95602	0.23796	0.29807	0.22	0.90989	0.21842	0.42453	0.88214	0.21834	
10k - 15k	130,614	0.92729	0.17917	0.29403	0.16	0.87377	0.19318	0.39329	0.82059	0.17218	
15k - 20k	94,331	0.89826	0.14421	0.29252	0.25	0.73658	0.14503	0.31807	0.76510	0.14369	
20k - 25k	73,038	0.86864	0.11991	0.28773	0.27	0.71864	0.12725	0.29741	0.71380	0.12322	
25k - 30k	58,775	0.83801	0.10137	0.29156	0.58	0.62907	0.09186	0.24849	0.66535	0.10714	
30k - 35k	48,710	0.80709	0.08684	0.28371	0.30	0.61032	0.09719	0.24277	0.62040	0.09419	
35k - 40k	41,539	0.77752	0.07555	0.28733	0.78	0.47275	0.05385	0.17421	0.58056	0.08388	
40k - 45k	35,917	0.74781	0.06602	0.28722	0.52	0.58135	0.07679	0.22171	0.54323	0.07498	
45k - 50k	31,528	0.71903	0.05807	0.28404	0.42	0.52471	0.07364	0.20177	0.50934	0.06742	
50k - 55k	27,940	0.69065	0.05120	0.28807	0.65	0.55995	0.06828	0.20992	0.47785	0.06074	
55k - 60k	24,984	0.66303	0.04523	0.28579	0.56	0.42228	0.05234	0.15806	0.44884	0.05485	
60k - 65k	22,444	0.63545	0.03984	0.28890	0.82	0.36133	0.03880	0.13198	0.42136	0.04943	
65k - 70k	20,297	0.60875	0.03508	0.28551	0.61	0.36762	0.04313	0.13577	0.39601	0.04457	
70k - 75k	18,366	0.58154	0.03061	0.28546	0.42	0.40716	0.05187	0.15329	0.37135	0.03993	
75k - 80k	16,696	0.55512	0.02657	0.28212	0.69	0.40919	0.04364	0.14677	0.34845	0.03568	
80k - 85k	15,175	0.52833	0.02275	0.28821	0.33	0.43899	0.06078	0.16978	0.32617	0.03160	**
85k - 90k	13,641	0.49826	0.01874	0.28056	0.38	0.43581	0.05543	0.16215	0.30222	0.02723	**
90k - 95k	12,083	0.46406	0.01447	0.27956	0.75	0.25916	0.02758	0.09232	0.27622	0.02250	**
95k - 100k	10,278	0.41901	0.00923	0.26503	1.03	0.20355	0.01676	0.06626	0.24378	0.01656	**

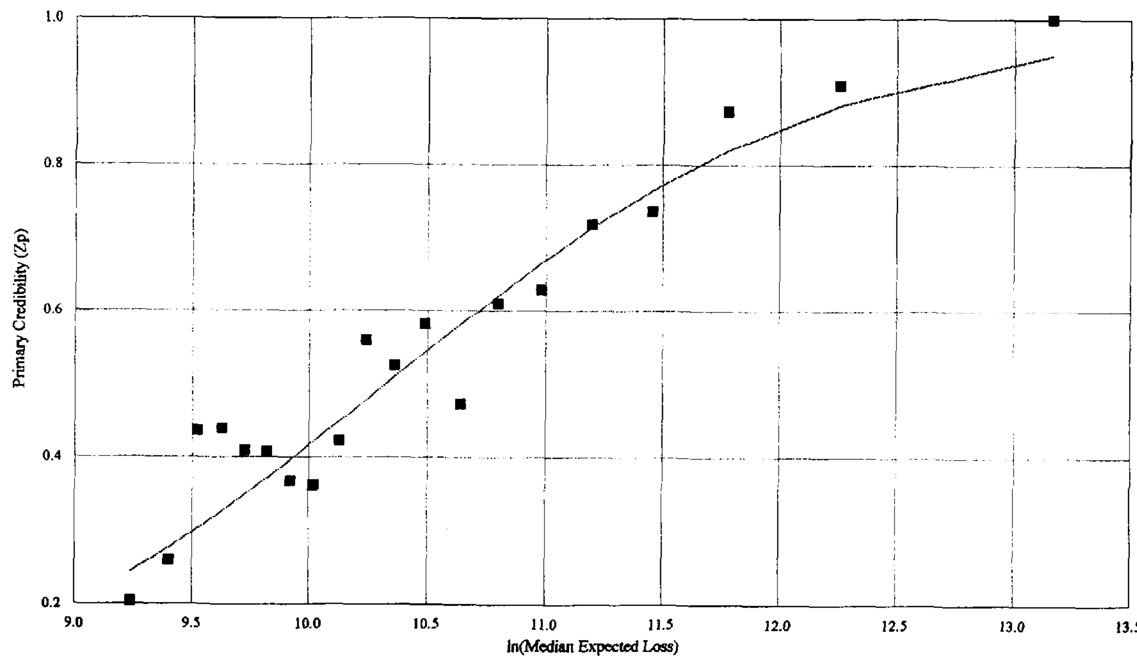
*Values along the ridge trace where excess credibility is maximized, with primary and excess credibilities bounded by [0,1].

**Data not used in credibility smoothing. Adjusted R^2 of fits: 0.93, Zp; 0.97, Ze.

CALIFORNIA EXPERIENCE RATING PLAN
DEVELOPMENT OF RATING VALUES / 1991 5th Report - Iteration 0
Primary Credibility / Zp = 1/(1 + exp[(10.3228 -X) / 0.958451)

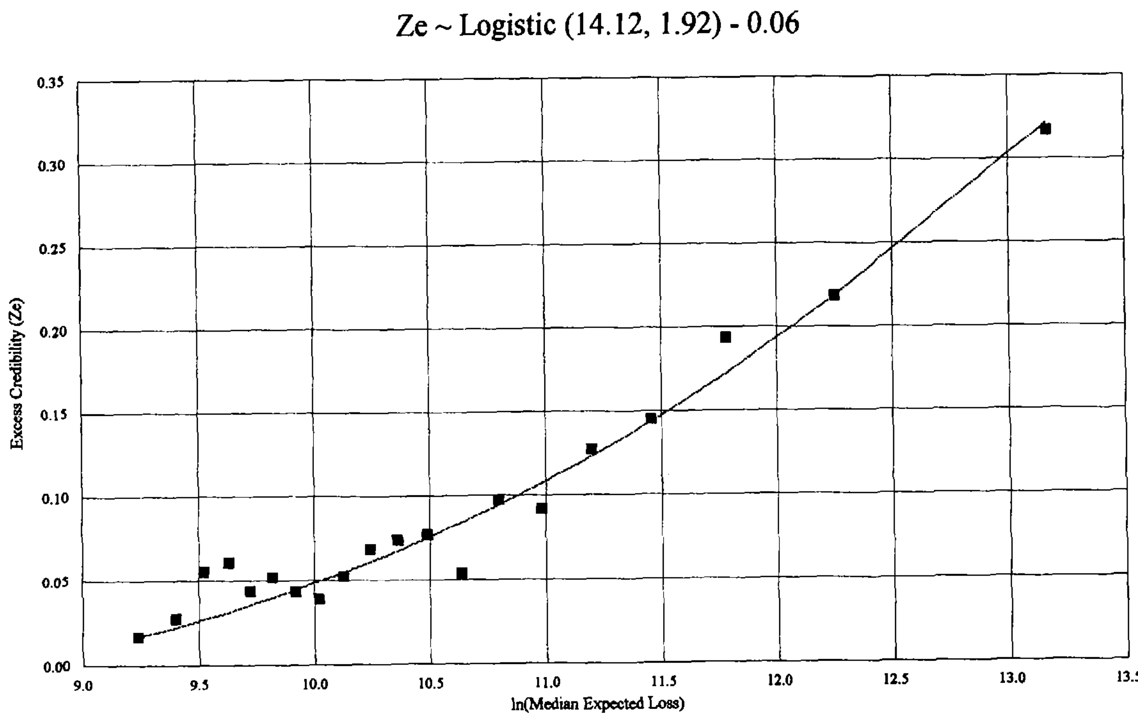
Exhibit 4
Part 1

Zp ~ Logistic (10.32, 0.96)



CALIFORNIA EXPERIENCE RATING PLAN
DEVELOPMENT OF RATING VALUES / 1991 5th Report - Iteration 0
Excess Credibility / Ze = [1/(1 + exp[(14.1151 -X) / 1.92436)] - 0.0569084

Exhibit 4
Part 2



DERIVATION OF B AND W VALUES FROM PRIMARY AND EXCESS CREDIBILITIES

Projection Year: 1991 5th Report - Iteration 0

1. $$Zp = \left(\frac{1}{1+\exp[(10.3228 - \ln(E))/0.9584)]} \right) \sim \text{Logistic}(10.3228, 0.9584)$$

2. $$Ze = \left(\frac{1}{1+\exp[(14.1151 - \ln(E))/1.9244)]} - 0.0569 \right) \sim \text{Logistic}(14.1151, 1.9244) - 0.0569$$

3. $$W = \frac{Ze}{Zp} \longrightarrow$$

$$W = \left(\frac{\dfrac{1}{1+\exp[(14.1151 - \ln(E))/1.9244)]} - 0.0569}{\dfrac{1}{1+\exp[(10.3228 - \ln(E))/0.9584)]}} \right)$$

$$W = \left(\frac{\dfrac{1}{1+\exp[(14.1151 - \ln(E))/1.9244)]}}{\dfrac{1}{1+\exp[(10.3228 - \ln(E))/0.9584)]}} - \frac{0.0569}{\dfrac{1}{1+\exp[(10.3228 - \ln(E))/0.9584)]}} \right)$$

$$W = \frac{1+\exp[(10.3228 - \ln(E))/0.9584)]}{1+\exp[(14.1151 - \ln(E))/1.9244)]} - 0.0569 \times (1+\exp[(10.3228 - \ln(E))/0.9584)])$$

4. $$Zp = \frac{E}{E+B}$$

Where E is the expected loss for the midpoint *of the range and Zp is the primary credibility* associated with E.

$$\longrightarrow \quad B = \frac{E(1 - Zp)}{Zp}$$

CALIFORNIA EXPERIENCE RATING PLAN
TABLE OF B AND W VALUES
Projection Year: 1991 at 5th Report - Iteration 0

Expected Losses		W	B
8,750 -	9,019	0.05	32,124
9,020 -	9,958	0.06	31,994
9,959 -	11,143	0.07	31,847
11,144 -	12,677	0.08	31,680
12,678 -	14,720	0.09	31,489
14,721 -	17,508	0.10	31,268
17,509 -	21,361	0.11	31,015
21,362 -	26,619	0.12	30,733
26,620 -	33,502	0.13	30,434
33,503 -	42,022	0.14	30,134
42,023 -	52,053	0.15	29,849
52,054 -	63,464	0.16	29,584
63,465 -	76,178	0.17	29,342
76,179 -	90,172	0.18	29,120
90,173 -	105,460	0.19	28,916
105,461 -	122,087	0.20	28,728
122,088 -	140,115	0.21	28,552
140,116 -	159,619	0.22	28,387
159,620 -	180,688	0.23	28,231
180,689 -	203,420	0.24	28,083
203,421 -	227,925	0.25	27,942
227,926 -	254,321	0.26	27,807
254,322 -	282,740	0.27	27,678
282,741 -	313,323	0.28	27,553
313,324 -	346,226	0.29	27,433
346,227 -	381,615	0.30	27,316
381,616 -	419,674	0.31	27,202
419,675 -	460,603	0.32	27,091
460,604 -	504,618	0.33	26,983
504,619 -	551,956	0.34	26,878
551,957 -	602,876	0.35	26,774
602,877 -	657,660	0.36	26,673
657,661 -	716,618	0.37	26,573
716,619 -	780,090	0.38	26,475
780,091 -	848,447	0.39	26,378
848,448 -	922,099	0.40	26,283
922,100 -	1,001,497	0.41	26,189
1,001,498 -	1,087,138	0.42	26,096
1,087,139 -	1,179,571	0.43	26,003
1,179,572 -	1,279,404	0.44	25,912
1,279,405 -	1,387,312	0.45	25,821
1,387,313 -	1,504,041	0.46	25,730
1,504,042 -	1,630,426	0.47	25,640
1,630,427 -	1,767,395	0.48	25,551
1,767,396 -	1,915,986	0.49	25,462
1,915,987 -	2,077,363	0.50	25,373
2,077,364 -	2,252,832	0.51	25,284
2,252,833 -	2,443,862	0.52	25,195
2,443,863 -	2,652,114	0.53	25,106
2,652,115 -	2,879,464	0.54	25,017
2,879,465 -	3,128,044	0.55	24,927
3,128,045 -	3,400,278	0.56	24,838
3,400,279 -	3,698,937	0.57	24,748
3,698,938 -	4,027,195	0.58	24,657
4,027,196 -	4,388,699	0.59	24,566
4,388,700 -	4,787,661	0.60	24,474
4,787,662 -	5,228,959	0.61	24,381
5,228,960 -	5,718,269	0.62	24,287
5,718,270 -	6,262,224	0.63	24,193
6,262,225 -	6,868,610	0.64	24,097
6,868,611 -	7,546,617	0.65	23,999
7,546,618 -	8,307,147	0.66	23,901
8,307,148 -	9,163,208	0.67	23,800
9,163,209 -	10,130,416	0.68	23,698
10,130,417 -	11,227,642	0.69	23,594
11,227,643 -	12,477,859	0.70	23,487
12,477,860 -	13,909,243	0.71	23,378
13,909,244 -	15,556,644	0.72	23,267
15,556,645 -	17,463,567	0.73	23,152
17,463,568 -	19,684,858	0.74	23,034
19,684,859 -	22,290,427	0.75	22,913
22,290,428 -	25,370,463	0.76	22,787
25,370,464 -	29,042,880	0.77	22,656
29,042,881 -	33,464,157	0.78	22,521
33,464,158 -	38,845,437	0.79	22,379
38,845,438 -	45,477,054	0.80	22,230
45,477,055 -	53,766,874	0.81	22,074
53,766,875 -	64,302,165	0.82	21,908
64,302,166 -	77,953,021	0.83	21,732
77,953,022 -	96,052,589	0.84	21,543
96,052,590 -	120,726,940	0.85	21,339
120,726,941 -	155,535,462	0.86	21,116
155,535,463 -	206,807,256	0.87	20,869
206,807,257 -	286,695,068	0.88	20,591
286,695,069 -	421,029,234	0.89	20,272
421,029,235 -	673,045,311	0.90	19,893
673,045,312 -	1,234,122,861	0.91	19,419
1,234,122,862 -	2,936,427,591	0.92	18,772

Exhibit 7

CALIFORNIA EXPERIENCE RATING PLAN
QUINTILES TESTS
Projection Year: 1991 5th Report

Iteration 0

Standard Loss Ratio

Indicated *Modification* Quintile	Expected Loss Quintiles: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.572	0.491	0.487	0.491	0.542	0.571
Low	0.625	0.550	0.528	0.491	0.633	0.603
Middle	0.629	0.589	0.567	0.593	0.633	0.621
High	0.638	0.641	0.618	0.630	0.628	0.642
Highest	0.622	0.639	0.657	0.633	0.743	0.627
All Risks	0.620	0.592	0.582	0.575	0.640	0.613

Manual Loss Ratio

Indicated Modification Quintile	Expected Loss Quintiles: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.394	0.373	0.401	0.427	0.486	0.426
Low	0.513	0.457	0.446	0.427	0.596	0.515
Middle	0.577	0.538	0.511	0.540	0.596	0.588
High	0.677	0.671	0.632	0.634	0.629	0.663
Highest	0.865	0.879	0.873	0.820	0.935	0.840
All Risks	0.598	0.583	0.574	0.571	0.644	0.595

Iteration 1

Standard Loss Ratio

Indicated Mod Quintile	Expected Loss Quintile: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.587	0.524	0.489	0.534	0.561	0.575
Low	0.632	0.550	0.547	0.534	0.587	0.621
Middle	0.634	0.597	0.599	0.589	0.687	0.628
High	0.635	0.626	0.609	0.629	0.636	0.635
Highest	0.614	0.628	0.631	0.602	0.701	0.618
All Risks	0.622	0.594	0.585	0.577	0.639	0.615

Manual Loss Ratio

Indicated Mod Quintile	Expected Loss Quintile: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.394	0.382	0.376	0.452	0.490	0.411
Low	0.513	0.439	0.444	0.452	0.520	0.530
Middle	0.578	0.541	0.533	0.516	0.648	0.577
High	0.677	0.661	0.633	0.645	0.646	0.663
Highest	0.866	0.892	0.877	0.828	0.938	0.851
All Risks	0.598	0.583	0.574	0.571	0.644	0.595

Iteration 2

Standard Loss Ratio

Indicated Modification Quintile	Expected Loss Quintiles: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.595	0.531	0.514	0.500	0.575	0.579
Low	0.632	0.558	0.544	0.568	0.592	0.623
Middle	0.635	0.599	0.611	0.601	0.667	0.629
High	0.635	0.626	0.601	0.618	0.633	0.633
Highest	0.613	0.620	0.621	0.583	0.710	0.615
All Risks	0.622	0.595	0.586	0.578	0.640	0.616

Manual Loss Ratio

Indicated Modification Quintile	Expected Loss Quintiles: Largest	Large	Middle	Small	Smallest	All Risks
Lowest	0.395	0.375	0.383	0.389	0.493	0.403
Low	0.513	0.440	0.420	0.473	0.522	0.520
Middle	0.579	0.541	0.544	0.523	0.636	0.576
High	0.676	0.663	0.629	0.642	0.648	0.664
Highest	0.866	0.893	0.886	0.825	0.940	0.854
All Risks	0.598	0.583	0.574	0.571	0.644	0.595

CALIFORNIA EXPERIENCE RATING PLAN Exhibit 8
ITERATIVE PARAMETER REFINEMENT
Projection Year: 1991 5th Report - Iteration 0

Expected Loss Quintiles

	Quintile #1		Quintile #2		Quintile #3		Quintile #4		Quintile #5		All Risks	
Projected Mod	Number of Risks	Std Loss Ratio	Number of Risks	Std Loss Ratio	Number of Risks	Std Loss Ratio	Number of Risks	Std Loss Ratio	Number of Risks	Std Loss Ratio	Number of Risks	Std Loss Ratio
0.0												
0.1												
0.2												
0.3												
0.4	2	1.013									2	1.013
0.5	11	0.339									11	0.339
0.6	167	0.496									167	0.496
0.7	1,703	0.573	165	0.385							1,868	0.569
0.8	3,666	0.583	4,840	0.497	1,453	0.423					9,959	0.561
0.9	3,782	0.643	4,567	0.566	8,470	0.528	9,835	0.491	4,507	0.530	31,161	0.603
1.0	3,249	0.623	3,366	0.602	3,433	0.597	3,894	0.672	13,247	0.633	27,189	0.622
1.1	2,485	0.658	2,335	0.655	2,507	0.627	2,460	0.602	3,010	0.624	12,797	0.652
1.2	1,646	0.594	1,681	0.642	1,568	0.640	1,556	0.625	2,232	0.724	8,683	0.610
1.3	1,086	0.594	1,078	0.657	936	0.671	904	0.651	1,104	0.749	5,108	0.613
1.4	763	0.615	700	0.600	611	0.616	535	0.601	628	0.713	3,237	0.615
1.5	512	0.658	462	0.640	368	0.649	323	0.644	330	0.827	1,995	0.658
1.6	296	0.608	269	0.618	239	0.632	189	0.528	185	0.932	1,178	0.616
1.7	212	0.757	167	0.617	141	0.740	125	0.547	111	0.925	756	0.731
1.8	134	0.689	130	0.708	93	0.649	63	0.931	51	0.678	471	0.695
1.9	75	0.603	82	0.620	48	0.878	40	0.904	41	0.603	286	0.631
2.0	61	0.548	44	0.682	34	0.752	24	0.569	22	0.839	185	0.575
2.1	41	0.625	29	0.596	32	0.790	19	0.441	9	0.833	130	0.630
2.2	23	0.703	24	0.698	21	0.892	11	1.318	8	0.262	87	0.717
2.3	18	0.694	14	0.383	16	0.530	6	1.118	7	1.174	61	0.657
2.4	13	0.487	16	0.760	9	0.203	3	2.489	4	0.663	45	0.516
2.5	15	0.657	10	0.896	6	1.807	5	0.220			36	0.695
2.6	6	0.725	5	0.888			1	0.154	1	0.000	13	0.714
2.7	4	0.977	4	0.139	4	0.789					12	0.657
2.8	3	1.146	2	0.856	2	0.699	1	0.635	3	2.743	11	1.188
2.9	7	0.629	2	0.425	1	0.050			2	0.432	12	0.589
3.0	2	0.841			1	0.000					3	0.832
>3.0	18	0.562	8	1.306	7	0.995	6	1.287	1	0.000	40	0.644
Total	20,000	0.620	20,000	0.592	20,000	0.582	20,000	0.575	25,503	0.640	105,503	0.613

Notes:

1. The Indicated Modification shown is the upper bound for the row. Therefore, the expected Indicated Mod for the 1.0 row is 0.95.

CALIFORNIA EXPERIENCE RATING PLAN
ITERATIVE PARAMETER REFINEMENT
Risk-Weighted Regression Output
Projection Year: 1991 5th Report - Iteration 0

Exhibit 9

Quintile 1

Weighted Regression Analysis

Dependent variable: Std_LR

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.568885	0.025802	22.048	0.0000
PROJ_MOD - 0.05	0.0485909	0.0253898	1.9138	0.0687

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	3.68357	1	3.68357	3.66	0.0687
Residual	22.1258	22	1.00572		
Total (Corr.)	25.8093	23			

R-squared = 14.2722 percent
R-squared (adjusted for d.f.) = 10.3755 percent
Standard Error of Est. = 1.00285
Mean absolute error = 0.0283059
Durbin-Watson statistic = 1.70045

Quintile 2

Weighted Regression Analysis

Dependent variable: Std_LR

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.395065	0.0394384	10.0173	0.0000
PROJ_MOD - 0.05	0.190755	0.0390622	4.88336	0.0001

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	44.7696	1	44.7696	23.85	0.0001
Residual	35.6697	19	1.87735		
Total (Corr.)	80.4394	20			

R-squared = 55.6564 percent
R-squared (adjusted for d.f.) = 53.3225 percent
Standard Error of Est. = 1.37017
Mean absolute error = 0.0340373
Durbin-Watson statistic = 0.869006

Quintile 3

Weighted Regression Analysis

Dependent variable: Std_LR

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.312573	0.0496612	6.29412	0.0000
PROJ_MOD - 0.05	0.262768	0.0493486	5.32473	0.0001

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	65.3039	1	65.3039	28.35	0.0001
Residual	39.1555	17	2.30326		
Total (Corr.)	104.459	18			

R-squared = 62.5161 percent
R-squared (adjusted for d.f.) = 60.3111 percent
Standard Error of Est. = 1.51765
Mean absolute error = 0.0292991
Durbin-Watson statistic = 1.43271

Quintile 4

Weighted Regression Analysis

Dependent variable: *Std_LR*

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.320195	0.0909611	3.52013	0.0031
PROJ_MOD - 0.05	0.251596	0.0910402	2 76357	0.0145

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	47.9631	1	47.9631	7.64	0.0145
Residual	94.2013	15	6.28009		
Total (Corr.)	142.164	16			

R-squared = 33.7378 percent
R-squared (adjusted for d.f.) = 29.3203 percent
Standard Error of Est. = 2.50601
Mean absolute error = 0.0543409
Durbin-Watson statistic = 2.20498

Quintile 5

Weighted Regression Analysis

Dependent variable: *Std_LR*

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.250208	0.0694848	3.60089	0.0032
PROJ_MOD - 0.05	0.383455	0.0684319	5.60346	0.0001

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	90.7514	1	90.7514	31.40	0.0001
Residual	37.5737	13	2.89029		
Total (Corr.)	128.325	14			

R-squared = 70.7199 percent
R-squared (adjusted for d.f.) = 68.4676 percent
Standard Error of Est. = 1.70008
Mean absolute error = 0.0288783
Durbin-Watson statistic = 2.03497

All Risks

Weighted Regression Analysis

Dependent variable: Std_LR

Parameter	Estimate	Standard Error	T Statistic	P-Value
CONSTANT	0.540786	0.0209312	25.8363	0.0000
PROJ_MOD - 0.05	0.0735404	0.0207073	3.55142	0.0016

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	28.3259	1	28.3259	12.61	0.0016
Residual	53.9003	24	2.24585		
Total (Corr.)	82.2262	25			

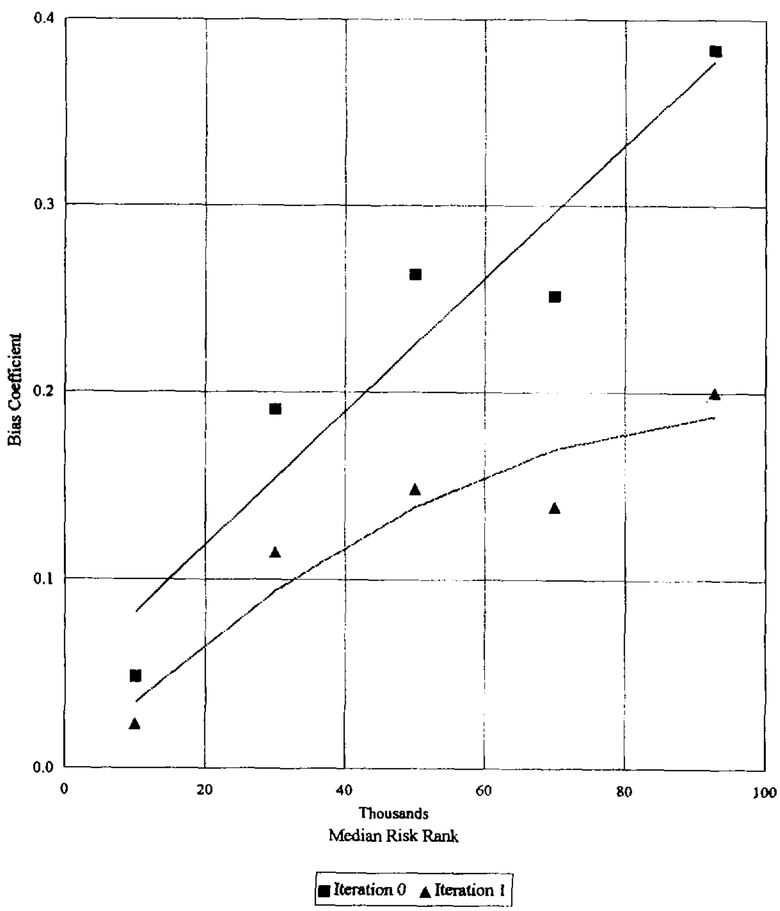
R-squared = 34.4488 percent
R-squared (adjusted for d.f.) = 31.7175 percent
Standard Error of Est. = 1.49861
Mean absolute error = 0.0158363
Durbin-Watson statistic = 1.6168

CALIFORNIA EXPERIENCE RATING PLAN Exhibit 10
ITERATIVE PARAMETER REFINEMENT
Projection Year: 1991 5th Report - Iteration 0

Expected Loss Quintile	Median Risk Rank	Bias Coefficient
Quintile # 1	10,000	0.048591
Quintile # 2	30,000	0.190755
Quintile # 3	50,000	0.262768
Quintile # 4	70,000	0.251596
Quintile # 5	92,752	0.383455
All Risks		0.073540

Regression Output:	
Constant	0.047528
Std Err of Y Est	0.044633
R Squared	0.899567
No. of Observations	5
Degrees of Freedom	3
X Coefficient(s)	3.55892E-06
Std Err of Coef.	6.86560E-07

Plot of Bias Coefficients



CALIFORNIA EXPERIENCE RATING PLAN — Exhibit 12

ADJUSTMENT OF MAXIMUM EXCESS CREDIBILITIES

Projection Year 1991 at 5th Report - Iteration 1

Risks	Iteration 0 Cred. Before Adjustment Zp	Iteration 0 Cred. Before Adjustment Ze	D Ratio Based on Actual Losses	Overall Crediblity Before Adj.	Indicated* Credibility Adjustments	Overall Credibility After Adj.**	Credibilities After Adjustment*** Θ	Credibilities After Adjustment*** Zp	Credibilities After Adjustment*** Ze	Credibilities After Adjustment*** Overall	Fitted Values Zp	Fitted Values Ze
1 - 5k	0.95084	0.32174	0.31619	0.52065	0.05643	0.55003	0.17	0.99999	0.31674	0.53277	0.99180	0.32759
5k - 10k	0.88214	0.21834	0.29807	0.41620	0.07422	0.44709	0.13	0.99840	0.21305	0.44714	0.97129	0.20602
10k - 15k	0.82059	0.17218	0.29403	0.36284	0.09201	0.39622	0.15	0.88164	0.19310	0.39555	0.94588	0.15591
15k - 20k	0.76510	0.14369	0.29252	0.32546	0.10981	0.36120	0.08	0.92664	0.12449	0.35914	0.91725	0.12664
20k - 25k	0.71380	0.12322	0.28773	0.29314	0.12760	0.33055	0.11	0.86620	0.11554	0.33152	0.88570	0.10650
25k - 30k	0.66535	0.10714	0.29156	0.26989	0.14540	0.30914	0.22	0.88408	0.07091	0.30800	0.85113	0.09125
30k - 35k	0.62040	0.09419	0.28371	0.24348	0.16319	0.28322	0.09	0.78779	0.08215	0.28235	0.81467	0.07935
35k - 40k	0.58056	0.08388	0.28733	0.22659	0.18099	0.26760	0.14	0.93206	0.00205	0.26928	0.77864	0.07013
40k - 45k	0.54323	0.07498	0.28722	0.20947	0.19878	0.25111	0.30	0.69411	0.07244	0.25100	0.74160	0.06237
45k - 50k	0.50934	0.06742	0.28404	0.19294	0.21658	0.23473	0.18	0.65941	0.06595	0.23451	0.70514	0.05592
50k - 55k	0.47785	0.06074	0.28807	0.18090	0.23437	0.22330	0.52	0.60997	0.06752	0.22378	0.66882	0.05034
55k - 60k	0.44884	0.05485	0.28579	0.16745	0.25217	0.20967	0.14	0.65065	0.03292	0.20946	0.63329	0.04550
60k - 65k	0.42136	0.04943	0.28890	0.15688	0.26996	0.19923	0.17	0.66953	0.00908	0.19988	0.59780	0.04115
65k - 70k	0.39601	0.04457	0.28551	0.14491	0.28776	0.18661	0.14	0.59118	0.02374	0.18575	0.56356	0.03729
70k - 75k	0.37135	0.03993	0.28546	0.13454	0.30555	0.17565	0.20	0.49474	0.04821	0.17568	0.52890	0.03368
75k - 80k	0.34845	0.03568	0.28212	0.12392	0.32334	0.16399	0.47	0.47507	0.04205	0.16422	0.49558	0.03042
80k - 85k	0.32617	0.03160	0.28821	0.11650	0.34114	0.15624	0.49	0.39471	0.05975	0.15629	0.46223	0.02734
85k - 90k	0.30222	0.02723	0.28056	0.10438	0.35893	0.14185	0.65	0.36987	0.05334	0.14215	0.42544	0.02409
90k - 95k	0.27622	0.02250	0.27956	0.09343	0.37673	0.12863	0.20	0.42198	0.01504	0.12881	0.38456	0.02064
95k - 100k	0.24378	0.01656	0.26503	0.07678	0.39452	0.10707	0.20	0.40402	0.00043	0.10739	0.33256	0.01641

* Credibility Adjustment = 0.047528 + (Rank of median risk) x (3.55892E-06). See Exhibit 10.

** Overall Credibility After Adjustment = Overall Credibility Before Adjustment x [1 + Indicated Credibility Adjustment].

*** Credibilities along the ridge trace with overall credibility closest to the "Overall Credibility After Adjustment" and with Primary and Excess Credibility values bounded by [0,1].

CALIFORNIA EXPERIENCE RATING PLAN Exhibit 13

SUMMARY OF PLAN EFFICIENCIES BY EXPECTED LOSS QUINTILES

Projection Year: 1991 5th Report

Manual Premium Weighted		Expected Loss Quintiles: Largest 20%	2nd Largest 20%	Middle 20%	2nd Smallest 20%	Smallest 20%	All Risks
Parameterized B & W Plan -1989 3rd		NA	NA	NA	NA	NA	NA
Frequency Only -1989 3rd		NA	NA	NA	NA	NA	NA
Promulgated Rating Values (based on 1989 3rd)		0.128994	0.042998	0.029201	0.020843	0.013164	0.068523
Parameterized B & W Plan (based on 1991 5th)	Starting Values	0.129106	0.039685	0.024801	0.017089	0.010145	0.066184
	Iteration 1	0.129792	0.042418	0.028301	0.019253	0.012138	0.068038
	Iteration 2	**0.130107**	**0.043756**	**0.029928**	**0.019647**	**0.011545**	**0.068829**
	Iteration 3	0.129575	0.044131	0.030589	0.020583	0.010485	0.068709

Risk Weighted		Expected Loss Quintiles: Largest 20%	2nd Largest 20%	Middle 20%	2nd Smallest 20%	Smallest 20%	All Risks
Parameterized B & W Plan -1989 3rd		0.074752	0.024968	0.010343	0.010181	0.007118	0.020767
Frequency Only -1989 3rd		0.081791	0.028444	0.015099	0.013181	0.008131	0.024437
Promulgated Rating Values (based on 1989 3rd)		0.067791	0.033602	0.025104	0.017707	0.009833	0.024833
Parameterized B & W Plan (based on 1991 5th)	Starting Values	0.067418	0.031215	0.021153	0.014610	0.007803	0.023358
	Iteration 1	0.068274	0.033614	0.024102	0.015783	0.009420	0.024758
	Iteration 2	**0.069529**	**0.034387**	**0.025760**	**0.017029**	**0.009400**	**0.025815**
	Iteration 3	0.069166	0.034830	0.026186	0.017744	0.008103	0.025577

NOTES:

Efficiency is measured as the proportionate reduction in total variance using the following formula:

$$\text{Efficiency} = \frac{E[(u-M)^2 - (u-F)^2]}{E[(u-M)^2]}$$

Where E[x] is the expected value function over all risks, u is the Empirical Modification (actual loss / expected loss), M is the Average Empirical Modification for all risks, and F is the Modification under the Plan. This measure of efficiency is discussed by Glenn Meyers in "An Analysis of Experience Rating," PCAS LXXII, 1985, p287. Larger values of efficiency indicate better reproduction of empirical experience.

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - All Risks

Exhibit 14
Part 1

Indicated Mod	Current Modification																																Total
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	
0.0																																	
0.1																																	
0.2																																	
0.3				1	1																												2
0.4					1																												1
0.5						27	1																										28
0.6						6	300	5																									311
0.7							127	3,956	1,016																								5,099
0.8								461	15,627	3,258																							19,346
0.9									525	24,001	862																						25,388
1.0										4,399	13,836	673																					18,908
1.1											349	9,596	983	188	137	2																	11,255
1.2												669	6,770	903	120	140	76	30	4	1													8,713
1.3												1	813	3,900	584	43		7	31	27	27	6	1		1								5,441
1.4													33	649	2,295	470	59	11			2	5	13	6	4								3,547
1.5														8	544	1,452	355	51	16						5	5	3	3					2,442
1.6															20	436	832	232	25	18	3							1		2	1	3	1,573
1.7															1	29	319	526	160	14	7	5										2	1,063
1.8																1	27	272	316	107	17	5	7	1								4	757
1.9																		14	141	200	78	15		4	4							1	457
2.0																		3	26	119	110	44	13	1	1	1	2						320
2.1																			3	24	89	71	36	11		1	2						237
2.2																			1		16	43	44	21	9	2		1					137
2.3																					4	15	42	32	16	1	4					1	115
2.4																				1	1	2	7	27	27	12	6	1				2	86
2.5																							2	6	17	16	12	4	5			1	63
2.6																							1	1	9	20	13	7	3	1			55
2.7																									5	10	6	9	7	2		1	40
2.8																										1	4	3	3	4	1	1	17
2.9																										1	1	4	4	2	1	1	14
3.0																											1	1	4	3	1	6	16
>3.0																													2	7	2	61	72
Total				1	2	33	428	4,422	17,168	31,658	15,047	10,939	8,599	5,648	3,701	2,573	1,668	1,146	723	511	354	211	166	110	98	70	54	34	28	21	6	84	105,503

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - Quintile #1

Exhibit 14
Part 2

Indicated	Current Modification																																
Mod	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	Total
0.0																																	
0.1																																	
0.2																																	
0.3				1	1																												2
0.4					1																												1
0.5						27	1																										28
0.6						6	299	3																									308
0.7							127	2,029	3																								2,159
0.8								412	2,997	18																							3,427
0.9									350	3,158	54																						3,562
1.0										223	2,750	123																					3,096
1.1											101	2,123	141																				2,365
1.2												49	1,443	141																			1,633
1.3													29	927	132																		1,088
1.4														13	596	137																	746
1.5															13	436	110																559
1.6																8	216	79	2														305
1.7																	3	166	69	1													239
1.8																		1	103	44	1												149
1.9																				54	32	3											89
2.0																				1	36	28											65
2.1																					2	26	18										46
2.2																							19	12	1								32
2.3																								12	9	1							22
2.4																									7	8							15
2.5																										4	10	1					15
2.6																											1	6	2				9
2.7																												3	4				7
2.8																													2	2	1		5
2.9																															1	1	2
3.0																															1	4	5
>3.0																																21	21
Total				1	2	33	427	2,444	3,350	3,399	2,905	2,295	1,613	1,081	741	581	329	246	174	100	71	57	37	24	17	13	11	10	8	2	3	26	20,000

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - Quintile #2

Exhibit 14
Part 3

Indicated	Current Modification																																
Mod	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	Total
0.0																																	
0.1																																	
0.2																																	
0.3																																	
0.4																																	
0.5																																	
0.6							1	2																									3
0.7								1,825	474																								2,299
0.8								49	4,139	108																							4,296
0.9									124	3,169	94																						3,387
1.0										157	2,534	150																					2,841
1.1											178	1,756	155																				2,089
1.2												169	1,303	106																			1,578
1.3													115	901	101	1																	1,118
1.4														96	574	93	1																764
1.5															69	355	56																480
1.6																58	252	52															362
1.7																	45	156	32														233
1.8																		33	96	26													155
1.9																			23	74	25												122
2.0																				20	46	9	1										76
2.1																					14	23	11										48
2.2																						10	13	6	1								30
2.3																						1	15	12	5								33
2.4																								7	9	3	3						22
2.5																									6	7	2	1					16
2.6																										3	7	1					11
2.7																											1	6	3	1			11
2.8																												2	1	2			5
2.9																													1	2			3
3.0																													1	2		1	4
>3.0																														1	1	12	14
Total							1	1,876	4,737	3,434	2,806	2,075	1,573	1,103	744	507	354	241	151	120	85	43	40	25	21	13	13	10	6	8	1	13	20,000

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - Quintile #3

Exhibit 14
Part 4

Indicated	Current Modification																															
Mod	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	Total
0.0																																	
0.1																																	
0.2																																	
0.3																																	
0.4																																	
0.5																																	
0.6																																	
0.7								102	539																								641
0.8									5,549	1,105																							6,654
0.9										3,005	205																						3,210
1.0										7	2,486	37																					2,530
1.1											66	2,064	20																				2,150
1.2												171	1,341	17																			1,529
1.3													217	745	6																		968
1.4														225	476	6																	707
1.5															188	307	6																501
1.6																161	166	3															330
1.7																1	132	100	2														235
1.8																		119	54														173
1.9																			53	34	2												89
2.0																			5	54	18												77
2.1																				4	41	9	1										55
2.2																					6	16	6	1									29
2.3																						5	14	2									21
2.4																							3	15	6								24
2.5																								3	7	3							13
2.6																									6	11	4						21
2.7																									1	8	4						13
2.8																											2						2
2.9																												4	2				6
3.0																													3	1			4
>3.0																													2	2		14	18
Total								102	6,088	4,117	2,757	2,272	1,578	987	670	475	304	222	114	92	67	30	24	21	20	22	10	4	7	3		14	20,000

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - Quintile #4

Exhibit 14
Part 5

Indicated	Current Modification																																
Mod	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	Total
0.0																																	
0.1																																	
0.2																																	
0.3																																	
0.4																																	
0.5																																	
0.6																																	
0.7																																	
0.8									2,775	1,795																							4,570
0.9										6,075	416																						6,491
1.0											2,000	195																					2,195
1.1											4	1,993	56																				2,053
1.2												271	1,320	33																			1,624
1.3												1	331	641	8																		981
1.4													25	251	392																		668
1.5														6	231	206	3																446
1.6															18	164	126	1															309
1.7															1	26	110	61															198
1.8																1	21	93	39														154
1.9																		13	53	18													84
2.0																		3	19	35	9												66
2.1																			3	15	27	6											51
2.2																			1		9	12	5										27
2.3																					4	9	8	4									25
2.4																					1	2	3	5	3								14
2.5																							1	3	2	1							7
2.6																							1		3	4	1						9
2.7																									4	2	1						7
2.8																										1	2	1					4
2.9																										1	1		1				3
3.0																											1	1					2
>3.0																														4	1	7	12
Total									2,775	7,870	2,420	2,460	1,732	931	650	397	260	171	115	68	50	29	18	12	12	9	6	2	1	4	1	7	20,000

CALIFORNIA EXPERIENCE RATING PLAN
INDICATED MODIFICATION VS CURRENT MODIFICATION
Projection Year: 1991 5th Report - Iteration 2
Number of Risks - Quintile #5

Exhibit 14
Part 6

Indicated	Current Modification																																
Mod	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0	>3.0	Total
0.0																																	
0.1																																	
0.2																																	
0.3																																	
0.4																																	
0.5																																	
0.6																																	
0.7																																	
0.8									167	232																							399
0.9									51	8,594	93																						8,738
1.0										4,012	4,066	168																					8,246
1.1												1,660	611	188	137	2																	2,598
1.2												9	1,363	606	120	140	76	30	4	1													2,349
1.3													121	686	337	42		7	31	27	27	6	1		1								1,286
1.4													8	64	257	234	58	11			2	5	13	6	4								662
1.5														2	43	148	180	51	16						5	5	3	3					456
1.6															2	45	72	97	23	18	3							1		2	1	3	267
1.7																2	29	43	57	13	7	5										2	158
1.8																	6	26	24	37	16	5	7	1								4	126
1.9																		1	12	20	19	12		4	4							1	73
2.0																			2	9	1	7	12	1	1	1	2						36
2.1																				5	5	7	6	11		1	2						37
2.2																					1	5	1	2	7	2		1					19
2.3																							5	2	2		4					1	14
2.4																				1			1		2	1	3	1				2	11
2.5																							1		2	1		2	5			1	12
2.6																								1		2			1	1			5
2.7																														1		1	2
2.8																																1	1
2.9																																	
3.0																																1	1
>3.0																																7	7
Total									218	12,838	4,159	1,837	2,103	1,546	896	613	421	266	169	131	81	52	47	28	28	13	14	8	6	4	1	24	25,503

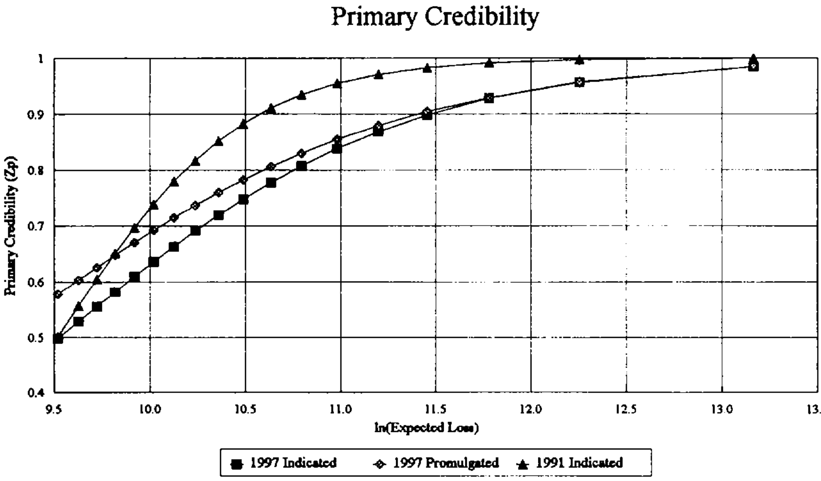
CALIFORNIA EXPERIENCE RATING PLAN
COMPARISON OF CREDIBLITIES
1997 Plan vs Projection Year 1991

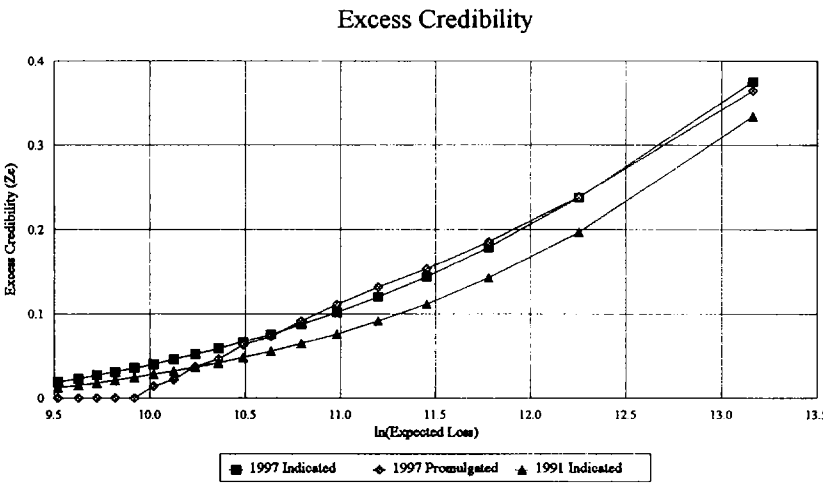
Exhibit 15

Risks	Median Exper. Period Expected Loss	1997 Experience Rating Plan Indicated Values Zp	1997 Experience Rating Plan Indicated Values Ze	1997 Experience Rating Plan Promulgated Values Zp	1997 Experience Rating Plan Promulgated Values Ze	1991 Iteration 2 (Final) Indicated Values Zp	1991 Iteration 2 (Final) Indicated Values Ze
1 - 5k	520,196	0.98381	0.37463	0.98381	0.36401	0.99949	0.33379
5k - 10k	209,397	0.95602	0.23796	0.95608	0.23902	0.99661	0.19710
10k - 15k	130,614	0.92729	0.17917	0.92888	0.18578	0.99101	0.14274
15k - 20k	94,331	0.89826	0.14421	0.90415	0.15371	0.98246	0.11189
20k - 25k	73,038	0.86864	0.11991	0.87957	0.13194	0.97051	0.09114
25k - 30k	58,775	0.83801	0.10137	0.85460	0.11110	0.95444	0.07574
30k - 35k	48,710	0.80709	0.08684	0.82967	0.09126	0.93411	0.06394
35k - 40k	41,539	0.77752	0.07555	0.80597	0.07254	0.91056	0.05493
40k - 45k	35,917	0.74781	0.06602	0.78221	0.06258	0.88269	0.04746
45k - 50k	31,528	0.71903	0.05807	0.75920	0.04555	0.85159	0.04132
50k - 55k	27,940	0.69065	0.05120	0.73643	0.03682	0.81698	0.03608
55k - 60k	24,984	0.66303	0.04523	0.71416	0.02142	0.77963	0.03158
60k - 65k	22,444	0.63545	0.03984	0.69178	0.01384	0.73896	0.02756
65k - 70k	20,297	0.60875	0.03508	0.66993	0.00000	0.69667	0.02405
70k - 75k	18,366	0.58154	0.03061	0.64747	0.00000	0.65105	0.02078
75k - 80k	16,696	0.55512	0.02657	0.62541	0.00000	0.60478	0.01787
80k - 85k	15,175	0.52833	0.02275	0.60278	0.00000	0.55647	0.01513
85k - 90k	13,641	0.49826	0.01874	0.57701	0.00000	0.50131	0.01228
90k - 95k	12,083	0.46406	0.01447	0.54716	0.00000	0.43858	0.00928
95k - 00k	10,278	0.41901	0.00923	0.50685	0.00000	0.35817	0.00565

*1997 Plan credibilities based on 1989 projection year.

CALIFORNIA EXPERIENCE RATING PLAN **Exhibit 16**
COMPARISON OF CREDIBLITIES
1997 Plan vs Projection Year 1991





CALIFORNIA EXPERIENCE RATING PLAN Exhibit 17

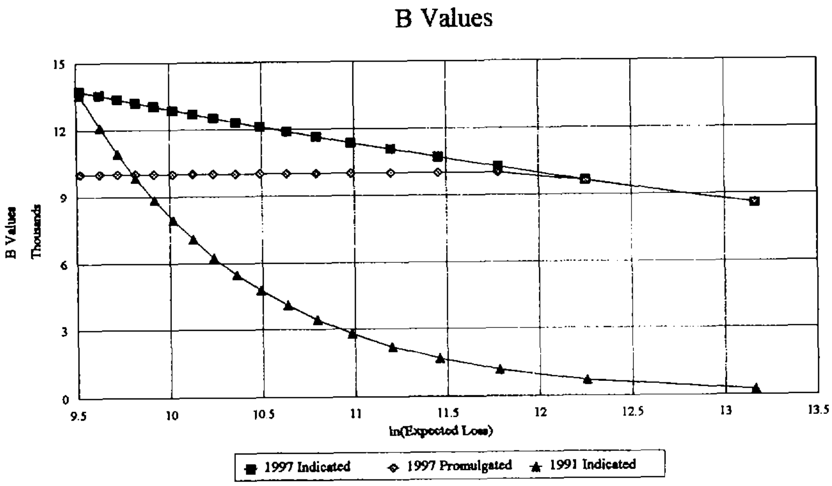
COMPARISON OF INDICATED AND 1997 PROMULGATED B & W PLAN

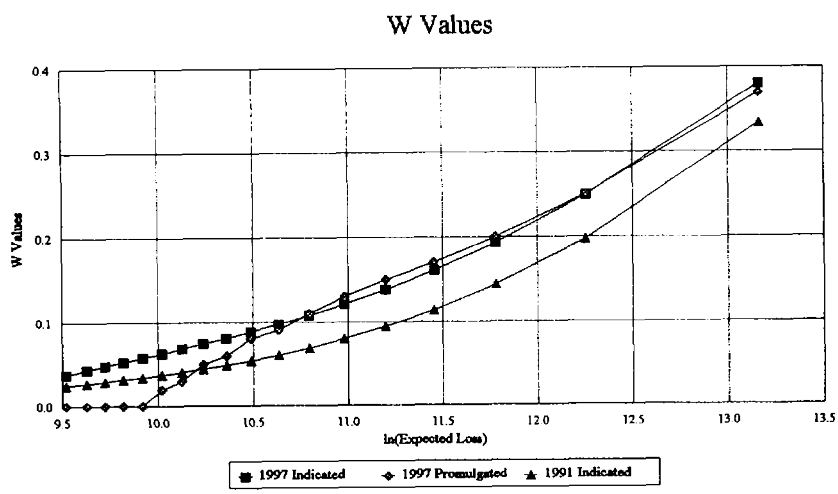
1997 Plan vs Projection Year 1991

	Median	1997 Experience Rating Plan				1991 Iteration 2 (Final)	
	Exper. Period	Indicated Values		Promulgated Values		Indicated Values	
Risks	Expected Loss	B	W	B	W	B	W
1 - 5k	520,196	8,558	0.381	8,562	0.37	267	0.334
5k - 10k	209,397	9,633	0.249	9,620	0.25	712	0.198
10k - 15k	130,614	10,242	0.193	10,000	0.20	1,185	0.144
15k - 20k	94,331	10,684	0.161	10,000	0.17	1,684	0.114
20k - 25k	73,038	11,045	0.138	10,000	0.15	2,219	0.094
25k - 30k	58,775	11,362	0.121	10,000	0.13	2,805	0.079
30k - 35k	48,710	11,642	0.108	10,000	0.11	3,436	0.068
35k - 40k	41,539	11,886	0.097	10,000	0.09	4,080	0.060
40k - 45k	35,917	12,113	0.088	10,000	0.08	4,773	0.054
45k - 50k	31,528	12,319	0.081	10,000	0.06	5,494	0.049
50k - 55k	27,940	12,514	0.074	10,000	0.05	6,259	0.044
55k - 60k	24,984	12,698	0.068	10,000	0.03	7,062	0.041
60k - 65k	22,444	12,876	0.063	10,000	0.02	7,928	0.037
65k - 70k	20,297	13,045	0.058	10,000	0.00	8,837	0.035
70k - 75k	18,366	13,216	0.053	10,000	0.00	9,844	0.032
75k - 80k	16,696	13,380	0.048	10,000	0.00	10,911	0.030
80k - 85k	15,175	13,547	0.043	10,000	0.00	12,095	0.027
85k - 90k	13,641	13,736	0.038	10,000	0.00	13,570	0.024
90k - 95k	12,083	13,955	0.031	10,000	0.00	15,467	0.021
95k - 00k	10,278	14,251	0.022	10,000	0.00	18,418	0.016

*1997 Plan credibilities based on 1989 projection year.

CALIFORNIA EXPERIENCE RATING PLAN Exhibit 18
COMPARISON OF INDICATED AND 1997 PROMULGATED B & W PLAN
1997 Plan vs Projection Year 1991





$$\text{Modification} = 1 + Z_p\left(\frac{A_p - Ep}{E}\right) \quad + \quad Z_e\left(\frac{A_e - Ee}{E}\right) \qquad \text{Formula 5}$$

From

$$Z_p = \frac{E}{E+B} \qquad \text{Formula 3}$$

$$Z_e = \frac{E}{E+J_e} = \frac{W \cdot E}{E+B} \qquad \text{Formula 4}$$

it follows that:

$$\begin{aligned}
& 1 + Z_p\left(\frac{A_p - Ep}{E}\right) + Z_e\left(\frac{A_e - Ee}{E}\right) \\
= \; & 1 + \left(\frac{E}{E+B}\right) \cdot \left(\frac{A_p - Ep}{E}\right) + \left(\frac{E}{E+J_e}\right) \cdot \left(\frac{A_e - E_e}{E}\right) \\
= \; & \left(\frac{E+B}{E+B}\right) + \left(\frac{A_p - Ep}{E+B}\right) + \left(\frac{A_e - E_e}{E+J_e}\right) \\
= \; & \frac{E+B+A_p-E_p}{E+B} + \frac{A_e - E_e}{E+J_e} \cdot \left(\frac{E+J_e}{E+B} \cdot \frac{E+B}{E+J_e}\right) \\
= \; & \frac{E+B+A_p-E_p+\left[(A_e - E_e) \cdot \left(\frac{E+B}{E+J_e}\right)\right]}{E+B} \\
= \; & \frac{A_p + B + \left(\frac{E+B}{E+J_e}\right) \cdot A_e + \left[(E - E_p) - E_e\left(\frac{E+B}{E+J_e}\right)\right]}{E+B} \\
= \; & \frac{A_p + B + W \cdot A_e + (1-W) \cdot E_e}{E+B} \qquad \text{Formula 1}
\end{aligned}$$

where:

$$W = \frac{E+B}{E+J_e} = \frac{Z_e}{Z_p}$$

Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio
0005	4.50	0.301	2116	5.45	0.271	3085	5.68	0.289	4112	1.23	0.328
0016	7.22	0.298	2117	8.57	0.282	3099	2.65	0.333	4114	5.44	0.310
0034	6.48	0.284	2121	3.02	0.366	3110	5.70	0.324	4130	6.10	0.316
0035	4.16	0.280	2142	4.71	0.313	3111	5.05	0.286	4133	5.17	0.272
0036	5.76	0.291	2150	8.09	0.337	3131	3.09	0.326	4150	2.23	0.324
0038	10.79	0.261	2163	4.15	0.317	3146	4.38	0.312	4239	3.56	0.281
0040	3.69	0.305	2211	9.88	0.267	3152	2.42	0.330	4240	4.82	0.312
0041	3.01	0.291	2222	13.79	0.358	3165	4.94	0.276	4243	3.04	0.350
0042	6.58	0.298	2362	8.44	0.311	3169	3.56	0.309	4244	4.93	0.305
0044	4.10	0.309	2402	5.40	0.305	3175	5.13	0.325	4250	4.38	0.334
0045	3.69	0.323	2413	7.82	0.286	3178	2.13	0.324	4251	5.41	0.308
0050	6.29	0.274	2501	3.48	0.327	3179	3.14	0.327	4279	5.88	0.299
0079	3.88	0.248	2532	5.05	0.259	3180	6.67	0.318	4283	4.82	0.296
0103	5.36	0.382	2570	7.68	0.308	3220	3.06	0.328	4297	0.62	0.305
0106	15.87	0.221	2571	7.49	0.303	3224	2.15	0.384	4299	3.11	0.331
0171	8.16	0.252	2576	6.52	0.315	3241	6.42	0.320	4304	4.73	0.334
0172	5.80	0.254	2578	7.80	0.307	3255	4.22	0.341	4312	4.77	0.274
0251	3.85	0.304	2585	5.44	0.324	3257	5.00	0.303	4351	0.77	0.415
0400	4.41	0.293	2586	3.60	0.287	3300	5.85	0.379	4354	2.47	0.318
0401	11.06	0.287	2623	13.06	0.322	3339	6.45	0.305	4360	1.15	0.326
1122	3.83	0.225	2660	8.72	0.282	3365	8.85	0.285	4361	1.78	0.341
1123	4.96	0.258	2683	7.89	0.322	3372	6.58	0.298	4362	1.27	0.278
1124	2.45	0.266	2688	5.98	0.294	3373	4.29	0.353	4410	6.35	0.302
1320	1.89	0.273	2702	12.92	0.226	3383	2.38	0.301	4414	1.66	0.455
1322	10.91	0.240	2710	9.13	0.296	3400	5.82	0.311	4420	10.54	0.297
1330	6.05	0.260	2731	6.14	0.290	3507	6.36	0.303	4431	1.98	0.420
1438	5.95	0.305	2759	7.44	0.305	3574	2.67	0.347	4432	3.78	0.356
1452	2.48	0.275	2790	2.65	0.373	3620	5.74	0.297	4470	5.03	0.293
1463	2.51	0.309	2797	8.70	0.304	3632	3.48	0.322	4478	5.57	0.301
1624	8.65	0.289	2806	8.28	0.312	3643	3.19	0.323	4511	1.21	0.305
1699	2.17	0.339	2812	6.47	0.296	3647	8.67	0.310	4557	3.08	0.335
1701	3.29	0.231	2819	10.49	0.276	3681	1.25	0.322	4558	3.82	0.318
1710	3.28	0.296	2842	8.65	0.283	3686	0.00	1.000	4567	6.30	0.250
1741	3.25	0.307	2881	8.39	0.316	3719	4.27	0.262	4568	3.65	0.188
1803	8.33	0.269	2883	9.23	0.315	3724	5.05	0.278	4611	3.55	0.308
1925	6.33	0.299	2915	9.62	0.256	3726	5.33	0.297	4635	2.27	0.325
2002	7.60	0.342	2923	4.09	0.355	3805	1.76	0.349	4665	6.24	0.334
2003	4.65	0.308	2960	8.98	0.245	3807	5.81	0.273	4670	5.08	0.339
2014	5.50	0.286	3004	5.70	0.275	3808	1.80	0.436	4683	7.51	0.334
2030	3.91	0.301	3018	2.53	0.249	3815	8.87	0.307	4692	1.40	0.306
2063	3.71	0.334	3022	4.51	0.286	3821	11.12	0.251	4717	2.64	0.378
2081	11.93	0.329	3028	3.25	0.350	3828	6.28	0.317	4720	5.34	0.288
2095	7.58	0.309	3030	9.28	0.269	3830	2.63	0.294	4740	2.37	0.296
2102	4.32	0.330	3040	11.16	0.277	4000	4.53	0.259	4757	2.79	0.324
2106	6.45	0.357	3060	6.26	0.314	4034	8.51	0.277	4771	2.69	0.271
2107	5.87	0.330	3066	4.52	0.323	4036	3.97	0.282	4828	4.79	0.314
2108	6.22	0.303	3070	1.04	0.346	4038	5.49	0.308	4829	2.29	0.319
2109	6.60	0.323	3076	6.30	0.313	4041	5.70	0.251	4922	1.52	0.360
2111	5.01	0.330	3081	9.10	0.295	4049	4.74	0.311	4983	4.23	0.332
2113	7.55	0.332	3082	3.89	0.341	4111	1.92	0.394	5020	3.39	0.275

Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio
5022	6.54	0.237	6237	3.27	0.243	7855	5.35	0.259	8350	4.14	0.270
5040	10.09	0.229	6251	7.13	0.279	8001	3.23	0.321	8387	3.96	0.295
5057	13.46	0.221	6252	10.86	0.218	8008	1.72	0.331	8388	5.77	0.294
5059	15.59	0.229	6254	3.15	0.392	8013	1.19	0.292	8389	4.14	0.298
5102	5.91	0.253	6306	4.58	0.242	8015	4.06	0.308	8390	5.80	0.337
5128	1.13	0.341	6319	4.69	0.229	8017	2.62	0.333	8391	3.07	0.314
5146	4.45	0.289	6325	4.85	0.238	8018	4.75	0.310	8392	4.98	0.312
5160	1.70	0.266	6361	4.39	0.250	8021	9.11	0.298	8393	3.64	0.275
5183	4.04	0.288	6364	5.70	0.281	8028	5.03	0.282	8397	5.14	0.294
5184	6.53	0.286	6400	9.24	0.289	8031	4.46	0.325	8400	3.59	0.233
5188	4.06	0.261	6504	4.82	0.321	8032	4.37	0.341	8500	9.99	0.251
5190	3.35	0.284	6834	5.27	0.308	8039	2.93	0.368	8601	0.65	0.301
5191	1.85	0.326	7133	2.35	0.315	8041	5.59	0.289	8604	2.37	0.226
5192	3.73	0.342	7198	6.11	0.334	8042	3.22	0.316	8631	11.92	0.261
5200	4.69	0.268	7207	9.55	0.288	8046	2.86	0.331	8710	8.50	0.363
5207	5.13	0.278	7219	8.14	0.242	8057	4.96	0.246	8719	2.79	0.332
5212	4.11	0.265	7248	2.03	0.117	8059	3.46	0.225	8720	2.80	0.240
5213	5.73	0.251	7272	8.27	0.174	8060	2.93	0.271	8729	1.27	0.216
5214	3.72	0.256	7332	6.59	0.314	8061	5.23	0.280	8741	0.26	0.281
5222	8.79	0.236	7360	9.13	0.273	8062	1.16	0.321	8742	0.60	0.305
5225	5.42	0.250	7365	8.04	0.265	8063	2.58	0.306	8745	4.02	0.320
5348	3.77	0.280	7382	7.63	0.299	8064	3.48	0.308	8748	0.84	0.266
5403	6.85	0.246	7392	6.34	0.299	8065	2.75	0.384	8755	1.36	0.210
5436	6.06	0.266	7403	3.28	0.374	8079	0.00	1.000	8800	3.62	0.323
5443	4.48	0.267	7405	1.04	0.371	8102	4.44	0.270	8803	0.23	0.321
5445	5.27	0.247	7409	5.73	0.193	8103	8.97	0.300	8804	3.74	0.263
5462	7.64	0.283	7410	4.66	0.284	8105	9.00	0.357	8806	4.47	0.341
5473	18.98	0.347	7413	1.43	0.385	8106	6.24	0.319	8807	0.50	0.326
5474	6.95	0.235	7419	2.27	0.461	8107	3.54	0.325	8808	0.62	0.317
5479	11.14	0.266	7421	2.11	0.375	8110	3.29	0.258	8810	0.43	0.322
5480	8.16	0.238	7424	2.95	0.319	8111	4.70	0.318	8813	0.52	0.312
5506	4.89	0.262	7426	0.31	0.571	8113	12.25	0.279	8817	0.00	0.551
5507	3.81	0.241	7428	2.14	0.330	8116	4.07	0.307	8818	0.68	0.334
5538	4.80	0.285	7429	12.22	0.333	8117	4.96	0.303	8820	0.41	0.280
5551	17.20	0.205	7500	0.15	0.887	8203	0.00	1.000	8822	0.56	0.337
5606	1.84	0.293	7515	1.72	0.272	8204	18.94	0.227	8823	4.79	0.278
5645	9.78	0.244	7520	3.44	0.288	8209	6.60	0.294	8827	4.49	0.264
5650	6.25	0.266	7538	8.34	0.222	8215	8.69	0.239	8829	6.02	0.290
5703	14.92	0.224	7539	3.57	0.257	8227	3.68	0.270	8830	1.90	0.338
5951	0.65	0.284	7580	2.09	0.303	8232	5.17	0.285	8831	2.92	0.321
6003	8.99	0.174	7600	1.79	0.310	8264	6.98	0.300	8834	0.91	0.289
6011	7.80	0.215	7601	21.12	0.202	8265	13.27	0.255	8838	1.01	0.313
6204	10.97	0.239	7605	4.05	0.317	8267	7.20	0.265	8839	0.69	0.306
6206	5.62	0.243	7606	7.48	0.308	8278	121.83	0.266	8840	0.59	0.298
6213	3.66	0.200	7610	0.61	0.356	8286	6.64	0.269	8868	1.04	0.309
6216	6.97	0.215	7706	3.97	0.292	8291	5.13	0.295	8875	1.05	0.273
6217	3.73	0.238	7707	1529.26	0.193	8292	9.13	0.282	8901	0.96	0.320
6223	2.15	0.384	7720	6.44	0.278	8293	12.38	0.252	9008	7.45	0.298
6233	4.87	0.238	7721	5.35	0.295	8304	7.37	0.270	9015	5.31	0.270
6235	12.87	0.244	7722	19.83	1.000	8324	5.45	0.285	9016	4.21	0.322

Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio	Class Code	Exp Loss Rate	D-Ratio
9031	4.19	0.284	9085	6.29	0.288	9185	25.57	0.290	9507	3.75	0.301
9043	1.89	0.295	9092	3.06	0.303	9220	5.47	0.302	9519	3.47	0.299
9048	4.03	0.309	9101	4.97	0.281	9402	5.85	0.246	9521	4.75	0.260
9050	6.03	0.318	9154	2.15	0.340	9403	7.45	0.273	9522	4.78	0.296
9053	2.61	0.325	9156	2.67	0.354	9410	1.78	0.240	9529	9.65	0.210
9060	4.14	0.291	9158	0.00	1.000	9420	5.04	0.252	9545	1.95	0.350
9061	2.78	0.323	9180	6.20	0.305	9422	4.19	0.298	9549	5.47	0.297
9066	4.51	0.275	9181	11.39	0.315	9424	6.55	0.275	9552	10.81	0.211
9070	5.76	0.279	9182	1.69	0.384	9426	8.13	0.221	9586	1.61	0.295
9079	3.64	0.350	9184	10.20	0.313	9501	5.07	0.284	9610	1.53	0.318
									9620	2.57	0.279

Benchmark Class Code	1991 Empirical D-Ratio	1991 Manual D-Ratio	Benchmark Class Code	1991 Empirical D-Ratio	1991 Manual D-Ratio
0016	0.30	0.32	7198	0.33	0.31
0042	0.30	0.34	7219	0.24	0.31
0172	0.25	0.32	8008	0.33	0.35
2003	0.31	0.33	8017	0.33	0.34
2501	0.33	0.35	8018	0.31	0.33
2883	0.31	0.34	8039	0.37	0.33
3632	0.32	0.33	8232	0.28	0.32
3681	0.32	0.34	8387	0.29	0.31
3830	0.29	0.39	8389	0.30	0.31
4478	0.30	0.32	8391	0.31	0.32
5183	0.29	0.30	8742	0.31	0.32
5190	0.28	0.31	8810	0.32	0.33
5200	0.27	0.32	8829	0.29	0.38
5213	0.25	0.30	8834	0.29	0.34
5403	0.25	0.30	9008	0.30	0.35
5445	0.25	0.32	9015	0.27	0.32
5474	0.23	0.29	9043	0.29	0.34
5551	0.21	0.28	9050	0.32	0.36
5645	0.24	0.30	9079	0.35	0.35
6217	0.24	0.29			

Draper and Smith [4, pp. 318-319] discuss a procedure developed by Hoerl and Kennard which we call Hoerl and Kennard's δ. The basic idea is to calculate an initial θ, $\theta(0)$, then, using the parameters corresponding to $\theta(0)$, calculate the next θ. This continues until

$$\text{Criterion} = \frac{\theta(j+1)-\theta(j)}{\theta(j)} \qquad \text{Hoerl and Kennard's } \delta$$

where Hoerl and Kennard's $\delta = 20\{\mathrm{trace}(\mathbf{Z'Z})^{-1}/r\}^{-1.30}$ and r is the number of parameters in the model. The trace of a matrix is the sum of the elements on the main diagonal. In our experience, this procedure did not work sometimes and in these situations we selected the θ corresponding to the minimum criterion. We term the final θ the indicated θ, $\theta(\mathrm{I})$. The procedure was performed for each group of 5,000. Sometimes the procedure resulted in selection of a θ for which Zp is greater than unity. Generally this happened only for the largest risks. As nearly full primary credibility is expected for these risks, this result was deemed to be within a reasonable variance about unity and did not justify rejecting the procedure for this reason alone. Though Hoerl and Kennard's δ generally gave a relatively stable pattern of results, the efficiencies were inferior to the Maximum Excess method.

CALIFORNIA EXPERIENCE RATING PLAN Appendix 5
PARAMETER REFINEMENT
Bias Adjustment Logic for the Quintiles Test Extension

Average is defined as a modification of unity and a standard loss ratio equal to the all risks combined standard loss ratio. Note that a risks modification is always bounded between this empirical modification and unity. Where a risk falls in this range is a function of credibility.

1. Risks with relatively good experience always have modifications less than unity. So,

   A) Good experience and a standard loss ratio lower than average
      => that the modification is too high.
         => credibility is too low.

   B) Good experience and a standard loss ratio higher than average
      => that the modification is too low.
         => credibility is too high.

2. Risks with relatively poor experience always have modifications greater unity. So,

   A) Poor experience and a standard loss ratio lower than average
      => that the modification is too high
         => credibility is too high.

   B) Poor experience and a standard loss ratio higher than average
      => that the modification is too low
         => credibility is too low.

If we order risks by their modifications then look at the pattern of the standard loss ratios, we may see:

Modification	Standard Loss Ratios	
< Unity (good experience)	Low	High
> Unity (poor experience)	High	Low
Correlation between modifications and SLRs	Positive (Direct)	Negative (Inverse)
Implies credibility is	Too Low	Too High

No pattern implies credibilities are in balance by experience.

COMPARISON OF HISTORICAL D-RATIOS FOR BENCHMARK CLASSES

Class	Manual D-Ratios by Policy Year								
Code	1998	1995	1991	1990	1989	1985	1980	1975	1970
0016	0.29	0.32	0.32	0.33	0.34	0.42	0.39	0.40	0.47
0042	0.30	0.32	0.34	0.34	0.35	0.44	0.38	0.42	0.47
0172	0.31	0.32	0.32	0.33	0.33	0.40	0.42	0.38	------
2003	0.33	0.34	0.33	0.35	0.36	0.42	0.42	0.42	0.51
2501	0.32	0.33	0.35	0.36	0.38	0.43	0.43	0.42	0.51
2883	0.30	0.31	0.34	0.34	0.36	0.42	0.45	0.41	0.51
3632	0.31	0.31	0.33	0.33	0.34	0.41	0.41	0.40	0.48
3681	0.31	0.31	0.34	0.34	0.36	0.41	0.41	0.37	0.46
3830	0.31	0.35	0.39	0.38	0.36	0.45	0.41	0.43	0.49
4478	0.30	0.34	0.32	0.33	0.35	0.40	0.42	0.41	0.50
5183	0.30	0.31	0.30	0.32	0.34	0.41	0.40	0.37	0.48
5190	0.26	0.28	0.31	0.33	0.34	0.38	0.39	0.38	0.46
5200	------	------	0.32	0.34	0.34	0.42	0.43	0.41	0.47
5213	0.30	0.31	0.30	0.31	0.31	0.42	0.40	0.40	0.48
5403	0.28	0.29	0.30	0.32	0.34	0.41	0.40	0.36	0.47
5445	------	------	0.32	0.32	0.35	0.42	0.44	0.44	0.50
5474	0.27	0.29	0.29	0.30	0.33	0.36	0.38	0.36	0.46
5551	------	------	0.28	0.30	0.31	0.39	0.43	0.35	0.46
5645	0.28	0.29	0.30	0.32	0.34	0.42	0.43	0.41	0.51
6217	------	------	0.29	0.31	0.33	0.38	0.39	0.35	0.44
7198	0.30	0.32	0.31	0.32	0.33	0.41	0.45	0.42	0.42
7219	0.30	0.32	0.31	0.32	0.33	0.41	0.41	0.41	0.50
8008	0.32	0.33	0.35	0.34	0.35	0.43	0.39	0.41	0.48
8017	0.31	0.33	0.34	0.34	0.35	0.42	0.40	0.39	0.48
8018	0.31	0.32	0.33	0.34	0.35	0.41	0.42	0.40	0.48
8039	0.35	0.35	0.33	0.33	0.36	0.42	0.39	0.39	0.48
8232	0.29	0.30	0.32	0.31	0.33	0.40	0.39	0.38	0.48
8387	0.31	0.30	0.31	0.32	0.34	0.39	0.40	0.39	0.48
8389	0.30	0.31	0.31	0.30	0.34	0.40	0.40	0.39	0.48
8391	0.30	0.31	0.32	0.33	0.34	0.41	0.42	0.41	0.46
8742	0.30	0.31	0.32	0.32	0.33	0.38	0.38	0.34	0.43
8810	0.32	0.33	0.33	0.34	0.35	0.40	0.41	0.38	0.46
8829	0.33	0.36	0.38	0.37	0.39	0.48	0.44	0.43	0.53
8834	0.33	0.34	0.34	0.35	0.36	0.42	0.41	0.38	0.48
9008	0.31	0.33	0.35	0.37	0.36	0.44	0.42	------	------
9015	0.29	0.30	0.32	0.33	0.33	0.39	0.40	0.39	0.49
9043	0.32	0.33	0.34	0.33	0.35	0.40	0.42	0.38	0.47
9050	0.31	0.33	0.36	0.37	0.38	0.41	0.41	0.39	0.51
9079	0.31	0.33	0.35	0.35	0.36	0.41	0.42	0.41	0.51

A Bayesian Approach to Negative Binomial Parameter Estimation

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A BAYESIAN APPROACH TO NEGATIVE BINOMIAL PARAMETER ESTIMATION

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Abstract

Some procedures that are used to calculate aggregate loss distributions and claim count distributions assume the claim count distribution is a negative binomial distribution. The parameters for the negative binomial distribution are often based on data from a small number of loss periods, and the estimates may have considerable error. A Bayesian procedure for parameter estimation allows the analyst to use some judgment when deriving the parameter estimate. This paper derives the Bayesian estimation procedure of the negative binomial parameter, p, under the assumption that the prior distribution for p is a beta distribution.

A BAYESIAN APPROACH TO NEGATIVE BINOMIAL PARAMETER ESTIMATION

Introduction

Consulting actuaries often calculate probability distributions of aggregate loss. Two methodologies, among others, are frequently used to arrive at the distribution of aggregate loss. One methodology is to use a theoretical distribution such as the log normal, gamma, or other distribution to approximate the aggregate loss distribution. A second methodology is to combine a distribution for the number of claims, usually the Poisson or negative binomial distribution, and a distribution of claim size. The use of either of these methodologies may require an estimate of the parameters of the negative binomial distribution. Usually, the actuary is working with a small number of years, and the parameter estimate for the claim count distribution may have considerable error. This paper provides a Bayesian procedure for estimating the negative binomial parameters that will provide some stability to the estimate.

When selecting a claim count distribution, an argument can be made that the negative binomial should be preferred to the Poisson in almost all situations. Two sets of assumptions are presented that lead to a negative binomial distribution as opposed to a Poisson distribution. First, assume that there are several populations that produce losses, for example, losses from the members of a pool or trust or from several divisions of a company. Next assume that the number of claims from each population has a Poisson distribution with parameter λ_r. If the λ's are gamma distributed, the claim count distribution for claims from all populations is negative binomial [1, p. 323-4]. A mathematically equivalent set of assumptions is to assume a Poisson distribution for the claim count distribution, and assume that the sampling errors in estimating the Poisson parameter have a gamma distribution. Then the claim count distribution including the parameter estimation error is negative binomial. In this situation the relationship between the negative binomial distribution and the Poisson distribution is analogous to the relationship between the t-distribution and the normal distribution. At least one of these sets of assumptions is reasonable in almost every situation involving the use of claim count distributions in producing a distribution of aggregate loss.

The following notation for number of claims, size of individual claim, and aggregate loss is adopted. Let n_t be the number of claims in period t; x_i is the size of the ith claim; and

$$y_t = \Sigma\, x_i,\ i = 1,\ldots,n_t \tag{1}$$

is the aggregate loss for period t. It is well known in the actuarial profession that the variance of the distribution of aggregate loss from a compound process of claim count and individual loss where claim size and the number of claims are independent is [1, p.319]

$$\sigma_y^2 = \mu_n\sigma_x^2 + \mu_x^2\sigma_n^2. \tag{2}$$

Thus, if the claim count distribution is negative binomial, the mean and variance of the aggregate distribution will depend on the parameters of the negative binomial. Whether a theoretical distribution is used to represent the aggregate distribution or the aggregate distribution is derived by combining the claim count distribution and the severity distribution, an estimate of the parameters of the claim count distribution is required.

<u>Negative Binomial</u>

There are several forms of the negative binomial. The form used here is

$$P(n) = \binom{n+k-1}{n} p^k (1-p)^n \qquad (3)$$

where $\mu_n = k(1 - p)/p$, and $\sigma_n^2 = k(1 - p)/p^2$. Solving these two relationships for p and k gives $p = \mu_n / \sigma_n^2$ and $k = \mu_n^2/(\sigma_n^2 - \mu_n)$. To emphasize the dependence on the parameter p, expression (3) may be written as

$$P(n|p) = \frac{\Gamma(n+k)}{\Gamma(n+1)\Gamma(k)} p^k (1-p)^n, \qquad (4)$$

where $$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx.$$

This is a conditional distribution for n given a specific value of the parameter p.

It is assumed that the actuary has made forecasts for the expected number of claims, μ_n, and the variance of the claim count distribution, σ_n^2. The method of moments can be applied using the relationships above to estimate the parameters p and k of the negative binomial distribution. However, this paper provides a procedure for modifying these estimates based on prior beliefs concerning these parameters. This procedure will provide some stability to the estimates and will cause extreme sample results from a small number of loss periods to be modified toward the actuary's preconceived notions which may be based on past experience.

<u>Prior Distribution</u>

Assume that the prior distribution of p is a beta distribution with parameters b and c. Thus, the prior distribution is [2;p. 255]

$$f(p) = \frac{p^{b-1}(1-p)^{c-1}}{B(b,c)}, \quad 0 < p < 1, \qquad (5)$$

where, $B(\alpha,\beta) = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1} dx = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$ is the beta function.

Let p_p represent the mean of this distribution. $p_p = b/(b+c)$. By choosing appropriate values for b and c, the actuary can have a subjective notion of the parameter, p, enter into the estimation process. For example, if b and c are both assigned values of one, the mean of the prior distribution of p, p_p is one-half; or if b=1 and c=3, p_p is one-fourth. The prior expected value will be modified based on the sample data for a final estimate which will be an average of the subjective prior estimate of the actuary and an estimate based on the sample data.

While the relative sizes of b and c determine the expected value of the prior distribution, the absolute size of the sum of b+c will influence the weight given to p_p when it is averaged with the estimate from the sample data. A procedure for determining the weight to be assigned the prior estimate is provided below. With this procedure the actuary can influence the relative weights given the prior estimate and the sample estimate based on the confidence placed in these estimates.

Posterior Distribution

To derive the posterior distribution of p, the joint distribution of p and the observed sample must first be calculated. Using (4), the probability of selecting the observed sample for a given value of p may written as

$$P(n_1,\ldots,n_T|p) = \prod_{t=1}^{T} \frac{\Gamma(n_t+k)}{\Gamma(n_t+1)\Gamma(k)} p^k (1-p)^{n_t} \tag{6}$$

$$= \frac{p^{Tk}(1-p)^{\Sigma n_t}}{\Gamma(k)^T} \prod_{t=1}^{T} \frac{\Gamma(n_t+k)}{\Gamma(n_t+1)},$$

where T is the number of loss periods contained in the sample. Multiplying (6) by the prior distribution for p, (5), gives the joint distribution of the observed sample and p.

$$P(n_1,\ldots,n_T,p) = \frac{1}{B(b,c)\Gamma(k)^T} p^{kT+b-1}(1-p)^{\Sigma n_t+c-1} \prod_{t=1}^{T} \frac{\Gamma(n_t+k)}{\Gamma(n_t+1)} \tag{7}$$

The probability distribution for an observed sample is obtained by integrating (7) over the entire range of p, 0<p<1. When the joint distribution of the sample observations and p is divided by the marginal distribution for the sample, the conditional distribution of p given the observed sample is obtained. Thus, dividing (7), the joint distribution, by (7) integrated with respect to p, the distribution for the observed sample, provides the conditional distribution for p given the observed sample as

$$f(p|n_1,\ldots,n_T) = \frac{p^{kT+b-1}(1-p)^{\Sigma n_t+c-1}}{\int_0^1 p^{kT+b-1}(1-p)^{\Sigma n_t+c-1}\,dp} \tag{8}$$

The denominator of (8) is a beta function, and may be written as $B[kT+b,\Sigma n_t+c]$, and (8) can be written as

$$f(p|n_1,\ldots,n_T) = \frac{p^{kT+b-1}(1-p)^{\Sigma n_t+c-1}}{B(kT+b,\Sigma n_t+c)}. \tag{8a}$$

(8a) is a beta distribution and is the posterior distribution of p given the observed sample.

For a squared error loss function the Bayes estimator of p is the mean of this posterior distribution.

$$E(p|n_1,\ldots,n_T) = p_B = \frac{\int_0^1 p^{kT+b}(1-p)^{\Sigma n_t+c-1}dp}{B(kT+b,\Sigma n_t+c)}$$

$$= \frac{B(kT+b+1,\Sigma n_t+c)}{B(kT+b,\Sigma n_t+c)}$$

$$= \frac{kT+b}{kT+b+c+\Sigma n_t}$$

$$= \frac{kT+b}{kT+b+c+Tm_n}. \tag{9}$$

To put the expression at the same level as the forecast value for the number of claims, the number of sample periods, T, times the forecast number, m_n, is substituted for the total number of claims in the sample period in the last step of the derivation.

An estimate of k is required to use expression (9) to calculate p_B. One choice is to use the estimates of μ_n and σ_n^2 from the sample data and the relationship $k = \mu_n^2/(\sigma_n^2 - \mu_n)$ to get an estimate of k for use in (9). Substituting this expression for k in (9) produces

$$p_B = \frac{b(1-p_s)+p_s m_n T}{(b+c)(1-p_s)+Tm_n} \tag{9a}$$

The Bayes estimate, p_B, is an average of the actuary's subjective estimate, $p_p = b/(b+c)$, and the sample data estimate, $p_s = m_n/s_n^2$. The weight given to these estimates depends partly on the sum b+c. Let w_p be the weight given to p_p and $w_s = 1 - w_p$ is the weight given to p_s. Then

$$w_p\, p_p + (1 - w_p)\, p_s = p_B. \tag{10}$$

Making substitutions for p_p and p_B and solving for w_p gives

$$w_p = (1-p_s)(b+c) / [(1-p_s)(b+c) + m_nT]. \tag{11}$$

The weight received by the prior estimate depends on the size of $(1-p_s)(b+c)$ relative to the forecast number of losses and the number of loss periods in the sample, m_nT, the weight given to the sample estimate.

The question to be answered is the value to be assigned to $(b+c)$. If an alternative question is answered, the value of $(b+c)$ will be determined. The relative weights of p_s and p_b can be made to depend only on the number of loss periods of sample data that is available. Suppose that it is determined that equal weights will be given to the two estimates when T_e periods of data are available. Under this assumption $(1-p_s)(b+c) = m_nT_e$, and the weight assigned to w_p is

$$\begin{aligned} w_p &= m_nT_e/(m_nT_e + m_nT) \\ &= T_e / (T_e + T). \end{aligned} \tag{12}$$

For example, if it is decided that the prior value and the sample value should receive equal weight when there are four years of sample data, then $T_e = 4$. When $T < 4$, the prior estimate receives more weight than the sample estimate, and vice versa when $T > 4$. The weights assigned to p_p and p_s by expression (12) for selected numbers of years in the sample are:

Number of Years in Sample:	2	4	6	8	10
Prior Estimate Weight (w_p):	.667	.500	.400	.333	.286
Sample Value Weight (w_s):	.333	.500	.600	.667	.714

When the value of T_e has been selected, the expression for estimating p_B becomes

$$p_B = (T_ep_p + Tp_s) / (T_e + T). \tag{13}$$

The estimate of k will need to be calculated such that the negative binomial distribution will have an expected value that equals the claim count forecast. The value for k may be obtained from the expression $k = p_Bm_n/(1-p_B)$, where m_n is the claim count forecast. Having estimates of p and k, the estimated variance of the claim count distribution is $s_n^2 = k(1 - p_B)/p_B^2$.

<u>An Example</u>

The first three columns of the following table show for each year in the sample the estimate of the ultimate number of claims and the exposure in terms of head count. The fourth column inflates the claim count to an exposure equivalent the exposure for the forecast period by multiplying the claim count for each year by the ratio of the forecast exposure to the loss year exposure. The variance for the sample data is calculated in the last column. The prior estimate of p is $p_p = .5$. p_s is the ratio of the expected claim count to the variance, $p_s = 298/881 = .338$. If $T_e = 4$, then using (13) the Bayes estimate is made as

$$p_B = \frac{[4(.5)+6(.338)]}{(4+6)} = .403.$$

Year	Claim Count	Exposure (Head count)	Inflated Claim Count	Squared Differences
1992	204	1282	334	1319
1993	226	1455	326	805
1994	219	1455	316	337
1995	226	1623	293	26
1996	214	1622	277	453
1997	240	1942	260	1465
Expected	298	2100	298	881

Using this estimate, k is calculated using the relationship $k=p_B m_n/(1-p_B) = .403(298)/.597 = 201$. Then the variance of the claim count distribution is estimated using $s_n^2 = k(1-p_B)/p_B^2 = 201(.597)/.403^2 = 739$.

A Bayesian procedure has been applied to produce an estimate of the variance of the claim count distribution that contains information relative to the analyst's prior estimates and experience. If experience adds valid information, this should be a more reliable estimate than one based solely on the sample data.

Summary

When calculating a probability distribution for aggregate losses for an accident year, an estimate of the variance of the claim count distribution is often required. When the number of accident years in the sample period is relatively small, an estimate based solely on the sample data is not reliable. This paper presents a methodology for estimating the variance of the claim count distribution that is based on a Bayesian procedure assuming a squared error loss function. The mean of the posterior distribution is the estimator that minimizes the expected squared error loss. The mean of the posterior distribution is a weighted average of the mean of the prior distribution and the sample estimate based on the sample moments. It is suggested that the actuary can choose the weights assigned to the prior estimate and the sample estimate that depend on the number of loss periods of sample data so that appropriate weights will be given to the two estimates.

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Random Effects Linear Statistical Models and Bühlmann-Straub Credibility

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Abstract

The definition and application of random effects linear models as a better alternative to empirical Bayesian credibility will be presented. A short review of Bühlmann-Straub credibility is contained in section 2. The author presents tractable formulas for quantifying the variability of credibility estimates. The variability of credibility estimates is produced without having to make distribution assumptions. However, if one assumes normality, hypothesis tests and confidence intervals can be constructed.

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Random Effects Linear Statistical Models and Bühlmann-Straub Credibility

1. INTRODUCTION

Credibility Theory allows casualty actuaries to answer the question: "How much of the difference in experience of a given policyholder is due to random variation in the underlying claims experience and how much is due to the fact that the policyholder is really a better or worse risk than the average for a given rating class?" [1:385]. Of course the difference among states, territories, and classes can also be the item of interest.

Random effects statistical models allow casualty actuaries to answer the above question and others. This model provides valuable information about the variability of the credibility estimate without having to assume a particular distribution. Moreover, the estimated parameters are Best Linear Unbiased Estimates of the true, but unknown parameters.

The definition of the linear model, applicable results, and several applications of the model will be presented. The estimation of K in the Whitney credibility formula $Z = E / (E+K)$, as proposed by Bühlmann-Straub, will also be reviewed.

2. REVIEW OF BÜLHMANN-STRAUB CREDIBILITY

Assume $Y_1, \ldots, Y_n$ are independent conditional on Θ, with common mean $\mu(\theta) = E(Y_i | \Theta = \theta)$, and with conditional variances $\upsilon(\theta)/E_i = Var(Y_i | \Theta = \theta)$. E_i is a known constant measuring exposure. The credibility formula, $Z_i = E_i / (E_i+K)$, is derived from those assumptions. When each risk has the same number of exposure units, the credibility formula is $Z = n / (n + K)$, where n is the number of observations per risk (Bühlmann credibility). The credibility estimate is equal to $\bar{Y}_i Z_i + (1-Z_i)\hat{\mu}$. $\bar{Y}_i$ is the weighted average for the ith risk, and $\hat{\mu}$ is the credibility weighted average of each $\bar{Y}_i$.

For an excellent history of credibility please see Venter's Credibility Chapter in *Foundations of Casualty Actuarial Science* [2:375-387]. Also see *Loss Models* [1:385-510] for a concise presentation of the principal components of credibility theory.

3. RANDOM EFFECTS LINEAR STATISTICAL MODELS

In using linear models to study the variability in data, we are interested in assigning that variability to the various categorizations of the data. The classifications that identify the source of observations are called factors. Usually there is more than one level of each factor. In classifying data in terms of factors and their levels, we are interested in the extent the different levels of each factor impacts the variable of interest. This is referred to as the *effect* of a level of a factor on that variable. The effects of a factor are classified as fixed effects or as random effects. *Fixed effects* are the effects from a finite set of levels of a factor that occur in the data and which are there because we are interested in them. *Random effects* are the effects from an infinite (usually) set of levels of a factor, of which only a random sample are deemed to occur in the data. For example, to test the tread-wear on sports cars compared to luxury sedans, four high perfomance tires were taken from each of seven batches. Whereas the effects due to type of car would be considered fixed effects (presumably we are interested in the particular cars), the effects due to batches would be considered a random sample of batches from some hypothetical, infinite population of batches. Since there is definite interest in the particular type of car used, the statistical concern is to estimate those car effects; they are fixed effects. Each individual tire is of no particular interest of itself to the trial; it is of interest solely as being one of twenty-eight tires randomly chosen from a larger population of tires. Inferences can and will be made about that population.

No assumption has been made that the type of cars are selected at random from a distribution of car types. In contrast, this kind of assumption has been made about the batch effects; interest in them lies in estimating the variance of those effects. Therefore the data are considered as having two sources of random variation: batch variance and, as usual, error variance. These two sources are known as *variance components*: their sum is the variance of the variable being observed. Models having only fixed effects are called fixed models. Models that contain both fixed and random effects are called mixed models. Finally, those having (apart from a single general mean common to all observations) only random effects are called random models.

Table 3.01 taken from [9:17] summarizes the mathematical characteristics of both classes of models.

Table 3.01

Characteristics of the fixed effects model and the random effects model for the 1-way classification

Characteristic	Fixed Effects Model	Random Effects Model
Model equation	$y_{ij} = \beta + \alpha_i + e_{ij}$	$y_{ij} = \beta + \alpha_i + e_{ij}$
Mean of y_{ij}	$E(y_{ij}) = \beta + \alpha_i$	$E(y_{ij} \mid \alpha_i) = \beta + \alpha_i$ $E(y_{ij}) = \beta$
α_i	Fixed, unknowable constant	$\alpha_i \sim$ i.i.d. $(0, \sigma_\alpha^2)$
e_{ij}	$e_{ij} = y_{ij} - E(y_{ij})$ $= y_{ij} - (\beta + \alpha_i)$ $e_{ij} \sim$i.i.d. $(0, \sigma_e^2)$	$e_{ij} = y_{ij} - E(y_{ij} \mid \alpha_i)$ $= y_{ij} - (\beta + \alpha_i)$ $e_{ij} \sim$i.i.d. $(0, \sigma_e^2)$
$E(e_{ij}\alpha_i)$	$E(e_{ij}\alpha_i) = \alpha_i E(e_{ij}) = 0$	$E(e_{ij}\alpha_i) = 0$, $\text{cov}(\alpha_i \alpha_k) = 0$
$\text{var}(y_{ij})$	$\text{var}(y_{ij}) = \sigma_e^2$	$\text{var}(y_{ij}) = \sigma_\alpha^2 + \sigma_e^2$
$\text{cov}(y_{ij}, y_{i'j'})$	$\text{cov}(y_{ij}, y_{i'j'})$ $= \left\{ \begin{array}{ll} \sigma_e^2 & \text{for } i = i' \text{ and } j = j' \\ 0 & \text{otherwise} \end{array} \right\}$	$\text{cov}(y_{ij}, y_{i'j'})$ $= \left\{ \begin{array}{ll} \sigma_\alpha^2 + \sigma_e^2 & \text{for } i = i' \text{ and } j = j' \\ \sigma_\alpha^2 & \text{for } i = i' \text{ and } j \neq j' \\ 0 & \text{otherwise} \end{array} \right\}$

To illustrate via the question posed in the introduction; assume the policyholders are in the same class. The classification plan attempts to group risks with similar characteristics. If the class plan is effective, the overall class mean, β, can be considered common to all the risks. Some risks will have better experience than the average risk and others will have worse. The actual experience of the risks are samples from a random variable representing the experience of each risk. How the actual experience of each risk varies from the class' average/expected experience can be modeled as the random effects, α_i, in the linear statistical model. Thus we seek to estimate the conditional mean $E(\beta + \alpha_i \mid \mathbf{Y})$, where $\mathbf{Y}$ is the vector of observed experience for the risks.

Random Effects Linear Statistical Models and Bühlmann-Straub Credibility

A matrix presentation of the random effects model which includes exposure weights follows:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{WA} + \mathbf{e}, \ \mathbf{A} \sim (\mathbf{O}, \sigma^2_A \mathbf{I}_r), \ \mathbf{e} \sim (\mathbf{O}, \sigma^2_e \mathbf{I}_N) \tag{3.1}$$

Y a Nx1 matrix, contains the experience; losses or number of claims. N is the total number of observations, N = rn, where n is the number of observations per risk, and r is the number of risks. **X** a Nx1 matrix, contains exposures. **W** is a Nxr block diagonal matrix of exposures.

β is the overall class mean and **A** is a rx1 matrix of random effects parameters, α_i, i = 1,...,r. From Table 3.01, the random effects are independent of the error terms **e**, and also independent across risks.

$$\text{Var}(\mathbf{Y}) = \mathbf{V} = \mathbf{W}\sigma^2_A\mathbf{W}' + \sigma^2_e(\text{Diag}(\mathbf{X})) \,, \tag{3.2}$$

V is block diagonal across risks and is the sum of the familiar terms: Variance of the Hypothetical Means (VHM), $\mathbf{W}\sigma^2_A\mathbf{W}'$ and Expected Value of the Process Variance (EVPV), $\sigma^2_e(\text{Diag}(\mathbf{X}))$.

If Var(**A**) and Var(**e**) are known, the estimators of β and **A** shown below are the best linear unbiased estimators (given the observations in **Y**). In most cases, Var(**A**) and Var(**e**) are also estimated. Hence, the following generalized least squares [5:597] formulas for $\hat{\beta}$ and $\hat{\mathbf{A}}$ produce empirical best linear unbiased estimators. Here, "best" means minimum mean squared error.

$$\hat{\beta} = (\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{Y}) \tag{3.3}$$

$$\hat{\mathbf{A}} = \hat{\sigma}^2_{\mathbf{A}} \mathbf{W}' \hat{\mathbf{V}}^{-1} (\mathbf{Y} - \mathbf{X}\hat{\beta}) \tag{3.4}$$

If $(\mathbf{X}' \hat{\mathbf{V}}^{-1} \mathbf{X})$ is singular, the Moore-Penrose (generalized) inverse,"-" instead of the regular inverse "-1", can be used in $\hat{\beta}$ [3:1-28].

Unbiased estimators of Var(**A**) and Var(**e**) are estimated by using a weighted analysis of variance (ANOVA) table and equating mean squares to their expected value [3:388-389, 452]. The derivation is presented below.

Table 3.02: Weighted ANOVA Table for a One Way Classification

Source of Varation	d.f.	Sum of Squares	Mean Square
Rows	r-1	$SSR = \sum_{i=1}^{r} E_i \, (\bar{Y}_i - \bar{Y})^2$	MSR = $^{\text{SSR}}/_{\text{r-1}}$
Residual Error	N-r	$SSE = \sum_{i=1}^{r} \sum_{j=1}^{n} E_{ij} \, (Y_{ij} - \bar{Y}_i)^2$	MSE = $^{\text{SSE}}/_{\text{N-r}}$

$$E(MSE) = \sigma^2_e \tag{3.5}$$

$$E(MSR) = \frac{1}{r-1}\left(\sum_{i=1}^{r} E_i - \sum_{i=1}^{r} E_i^2 / \sum_{i=1}^{r} E_i\right)\sigma^2_A + \sigma^2_e \tag{3.6}$$

Substituting the estimate of σ^2_e into equation (3.7) produces an unbiased estimator of $\sigma^2_{\mathbf{A}}$.

$$\hat{\sigma}^2_{\mathbf{A}} = \left[\sum_{i=1}^{r} E_i - \sum_{i=1}^{r} E_i^2 / \sum_{i=1}^{r} E_i\right]^{-1} \left[\sum_{i=1}^{r} E_i(\bar{Y}_i - \bar{Y})^2 - \hat{\sigma}^2_e(r-1)\right] \tag{3.7}$$

It turns out equation (3.7) is the same formula for the estimated variance of the hypothetical means found in Herzog [4] and Klugman *et al* [1]. These estimates are used in $\hat{\mathbf{V}}$ and the estimates of β and **A** are then produced.

The variance-covariance matrix, $\hat{\mathbf{C}}$, of $\hat{\beta}$ and $\hat{\mathbf{A}}$ can be used to analyze the variability of linear combinations of $\hat{\beta}$ and $\hat{\mathbf{A}}$.

$$\mathrm{Cov}(\hat{\beta},\hat{\mathbf{A}}) = \hat{\mathbf{C}} = \begin{bmatrix} \mathbf{X}'\Sigma_e^{-1}\mathbf{X} & \mathbf{X}'\Sigma_e^{-1}\mathbf{W} \\ \mathbf{W}'\Sigma_e^{-1}\mathbf{X} & \mathbf{W}'\Sigma_e^{-1}\mathbf{W}+\Sigma_{\mathbf{A}}^{-1} \end{bmatrix}^{-} \tag{3.8}$$

$\Sigma_e = \hat{\sigma}_e^2(\mathrm{Diag}(\mathbf{X}))$ and $\Sigma_{\mathbf{A}} = \hat{\sigma}_{\mathbf{A}}^2\mathbf{I}_r$.

If the reasonable assumption that $\mathbf{A} \sim \mathbf{N}(\mathbf{O},\sigma_{\mathrm{A}}^2\mathbf{I}_r)$ and $\mathbf{e} \sim \mathbf{N}(\mathbf{O},\sigma_e^2\mathbf{I}_N)$ is invoked, then hypothesis tests and confidence intervals of linear combinations of the parameters can be evaluated. For example, the following hypothesis test

$$\mathrm{H_o}:\mathbf{L}\begin{bmatrix}\hat{\beta}\\ \hat{\mathbf{A}}\end{bmatrix}=0 \quad \text{compared to} \quad \mathrm{H_a}:\mathbf{L}\begin{bmatrix}\hat{\beta}\\ \hat{\mathbf{A}}\end{bmatrix}\neq 0$$

can be performed by calculating the following t-statistic, $t = \dfrac{\mathbf{L}\begin{bmatrix}\hat{\beta}\\ \hat{\mathbf{A}}\end{bmatrix}}{\sqrt{\mathbf{L}\hat{\mathbf{C}}\mathbf{L}'}}$. This t-statistic has degrees of freedom, N-rank($\mathbf{X}$). If a confidence interval is of interest, then use $\mathbf{L}\begin{bmatrix}\hat{\beta}\\ \hat{\mathbf{A}}\end{bmatrix}\pm t_{\alpha/2}\sqrt{\mathbf{L}\hat{\mathbf{C}}\mathbf{L}'}$. In addition, the coefficient of variation (CV) of the estimates can be used to assess variability without making the normality assumption.

4. APPLICATIONS

The first application, like Halliwell's [6] paper, uses an example from the *Foundations of Casualty Actuarial Science* [2:433]. $\mathbf{Y}$ contains six pure premiums for nine risks, all with the same number of exposure units. The objective is to calculate credibility weighted pure premiums for each state, i.e., the predicted pure premium for each risk given all the pure premiums. The overall mean will serve as the fixed effect across risks, and the individual experience is the random effects. The model and the results are presented in Exhibits 1- 2.

First, σ^2_ε and σ^2_A are estimated from equations (3.5) and (3.7). Next, these values are used in $\hat{\mathbf{V}}$ to produce $\hat{\beta}$ and $\hat{\mathbf{A}}$ in Exhibit 2. Each $\mathbf{L}_i$, $\hat{\beta}$ and $\hat{\mathbf{A}}$ is used to calculate each value in $\hat{\mathbf{Y}}$. Lastly, $\hat{\mathbf{C}}$ is used conduct significance tests of the linear combinations of the parameters. Each risk parameter combined with the fixed effect is significantly different from 0 at the 5.0% level. The key addition to this analysis is the variance of the linear combination of the mean and random effects. The variability of the credibility estimates is now quantified; via the confidence interval and the coefficient of variation. T-tests of each risk parameter, $\hat{\mathbf{A}}$, can also be calculated by redefining each $\mathbf{L}_i$, starting with 0 instead of 1. Each risk parameter and all risk parameters together are not significantly different from 0. If a particular risk parameter is significant, chances are that risk(s) should be reclassified; remember $\mathbf{A} \sim (\mathbf{O}, \sigma^2_A)$. The credibility estimates are also provided in Exhibit 1. There should be no surprise that the random effects model produced the same values as the credibility weighted estimates.

Another example using varying exposures is the case study presented in *Loss Models* [1:504]. In Exhibit 3, four years of claims and exposures are presented for professional liability coverage of life / health, pension, and property / liability actuaries. The objective is to calculate a credibility weighted frequency for each group of actuaries, i.e., the predicted frequency for each type of liability coverage given all the observed frequencies. The same steps as in example 1 are followed.

However, two credibility estimates are calculated; one using a weighted average for the complement and the other using a credibility weighted average of each Y_i as the complement. The credibility weighted average was introduced in *Loss Models* [1:468] so that the total experience is reproduced using the credibility estimates; 221 claims. Notice that $\hat{\mu}$ and $\hat{\beta}$ are the same and both differ from the weighted average of the individual frequencies. The variability of the frequency predictions again are a valuable addition to the analysis of this data.

Last, the method was applied in the initial stages of designing a frequency based experience rating system for smaller workers compensation risks. Again, the objective is to calculate a credibility weighted frequency for each risk. Data for State D is partitioned among risks in a particular class code where their 3 year average earned premium is between 3,000 and 5,000. The individual experience of each group is modeled as random effects. The data and results are in Exhibit 4. **Y** contains first, second and third reports of the number of claims for 22 risks. **X** contains the payroll (in hundreds). Again, the random effects linear model produced the same frequency as the credibility model.

Now for a few directions on the analysis that can be performed. Risk 16 has the highest credibility, but it also has the highest CV. As a result of the high CV and no claims, it fails the t-test. Risk 11 has the smallest credibility, and it also fails the t-test. The credibilities of both these risks are driven primarily by volume: Risk 16 the most, Risk 11 the least. Risk 12 has the smallest CV and above average credibility. Risk 12 has produced one claim for each year while its exposures have been relatively steady. All claim free risks fail the t-test, while all risks with at least one claim pass the t-test. These results make intuitive sense, because failing the t-test suggests that the predicted frequency is not significantly different from zero. All the claim free risks have a predicted frequency less than the average but not equal to zero. The CV and confidence intervals provide an objective quantification of the variability underlying the potential frequencies. For instance, the upper end point of the confidence interval for Risk 16 is 49% higher than the overall frequency. This type of analysis aids the use of judgment needed to place swing limits on the experience modification for the small risks.

5. CONCLUSION

Credibility models are only a subset of the applications of random effects linear models to actuarial science. This paper provides a complete method for quantifying the variability of credibility estimates. The random effects model is relevant wherever credibility is required. Hopefully, others will see the great benefit of this technique, and start the climb out of the Flatlands regarding our statistical modeling skills.

Random Effects Linear Statistical Models and Bühlmann-Straub Credibility

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EXHIBIT 1

Risk	Y	X	W								
1	0.430	1	1								
1	0.375	1	1								
1	2.341	1	1								
1	0.175	1	1								
1	1.016	1	1								
1	0.466	1	1								
2	0.247	1		1							
2	1.587	1		1							
2	1.939	1		1							
2	0.712	1		1							
2	0.054	1		1							
2	0.261	1		1							
3	0.661	1			1						
3	0.237	1			1						
3	0.063	1			1						
3	0.250	1			1						
3	0.602	1			1						
3	0.700	1			1						
4	0.182	1				1					
4	0.351	1				1					
4	0.011	1				1					
4	0.022	1				1					
4	0.019	1				1					
4	0.252	1				1					
5	0.311	1					1				
5	0.664	1					1				
5	1.002	1					1				
5	0.038	1					1				
5	0.370	1					1				
5	2.502	1					1				
6	0.301	1						1			
6	0.253	1						1			
6	0.044	1						1			
6	0.109	1						1			
6	2.105	1						1			
6	0.891	1						1			
7	0.219	1							1		
7	1.186	1							1		
7	0.431	1							1		
7	1.405	1							1		
7	0.241	1							1		
7	0.804	1							1		
8	0.002	1								1	
8	0.058	1								1	
8	0.235	1								1	
8	0.018	1								1	
8	0.713	1								1	
8	0.208	1								1	
9	0.796	1									1
9	0.260	1									1
9	0.932	1									1
9	0.857	1									1
9	0.129	1									1
9	0.349	1									1

Var(e)	Var(A)	K	Zi	Risk	$\bar{Y}_i$	Credibility Weighted Pure Prem.
0.35701	0.00669	53.33244	0.10113	1	0.80050	0.58675
				2	0.80000	0.58670
				3	0.41883	0.54815
				4	0.13950	0.51991
				5	0.81450	0.58817
				6	0.61717	0.56821
				7	0.71433	0.57804
				8	0.20567	0.52660
				9	0.55383	0.56181
				$\bar{Y}$	0.56270	

EXHIBIT 2

B	Risk	A	L1'	L2'	L3'	L4'	L5'	L6'	L7'	L8'	L9'
			1	1	1	1	1	1	1	1	1
0.563	1	0.024	1	0	0	0	0	0	0	0	0
	2	0.024	0	1	0	0	0	0	0	0	0
	3	-0.015	0	0	1	0	0	0	0	0	0
	4	-0.043	0	0	0	1	0	0	0	0	0
	5	0.025	0	0	0	0	1	0	0	0	0
	6	0.006	0	0	0	0	0	1	0	0	0
	7	0.015	0	0	0	0	0	0	1	0	0
	8	-0.036	0	0	0	0	0	0	0	1	0
	9	-0.001	0	0	0	0	0	0	0	0	1

E(A) = -8.0E-07

C

0.007355	-0.000744	-0.000744	-0.000744	-0.000744	-0.000744	-0.000744	-0.000744	-0.000744	-0.000744
-0.000744	0.006092	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075
-0.000744	0.000075	0.006092	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075
-0.000744	0.000075	0.000075	0.006092	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075
-0.000744	0.000075	0.000075	0.000075	0.006092	0.000075	0.000075	0.000075	0.000075	0.000075
-0.000744	0.000075	0.000075	0.000075	0.000075	0.006092	0.000075	0.000075	0.000075	0.000075
-0.000744	0.000075	0.000075	0.000075	0.000075	0.000075	0.006092	0.000075	0.000075	0.000075
-0.000744	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.006092	0.000075	0.000075
-0.000744	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.006092	0.000075
-0.000744	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.000075	0.006092

Risk	Predicted Pure Prem.	Var of Pure Prem.	Coeff of Variation	t-statistic	t 0.025	Degrees of Freedom	Confidence Interval Lower pt	Upper pt
1	0.58675	0.01196	0.18639	5.36524	2.00575	53	0.36740	0.80610
2	0.58670	0.01196	0.18640	5.36478	2.00575		0.36735	0.80605
3	0.54815	0.01196	0.19951	5.01232	2.00575		0.32880	0.76751
4	0.51991	0.01196	0.21035	4.75402	2.00575		0.30055	0.73926
5	0.58817	0.01196	0.18594	5.37818	2.00575		0.36881	0.80752
6	0.56821	0.01196	0.19247	5.19571	2.00575		0.34886	0.78756
7	0.57804	0.01196	0.18920	5.28556	2.00575		0.35869	0.79739
8	0.52660	0.01196	0.20768	4.81520	2.00575		0.30725	0.74595
9	0.56181	0.01196	0.19466	5.13715	2.00575		0.34245	0.78116

EXHIBIT 3

Group	Year	Y	X	W		
LH	1990	20	853	853		
LH	1991	14	1,105	1,105		
LH	1992	16	1,148	1,148		
LH	1993	21	1,270	1,270		
P	1990	27	1,446		1,446	
P	1991	35	1,780		1,780	
P	1992	36	1,717		1,717	
P	1993	24	2,065		2,065	
PL	1990	5	639			639
PL	1991	8	725			725
PL	1992	4	685			685
PL	1993	11	864			864
	Total	221	14,297	4,376	7,008	2,913

Var(e)	Var(A)	K	Group	Zi	Weighted Average Frequency	Credibility Weighted Frequency	û	Credibility Weighted Frequency, û
0.0209424	0.0000097	2151.668	L/H	0.67038	0.01622	0.01597	0.01478	0.01575
			P	0.76509	0.01741	0.01695		0.01679
			P/L	0.57516	0.00961	0.01210		0.01181
			Total Weighted Frequency		0.01546			
					Total Claims	224		221

B	Group	A	L1'	L2'	L3'
0.014784			1	1	1
	L/H	0.00097	1	0	0
	P	0.00201	0	1	0
	P/L	-0.00297	0	0	1

E(A) = 0.000674

C

4.8408E-06	-3.245E-06	-3.704E-06	-2.784E-06
-3.245E-06	5.3837E-06	2.4828E-06	1.8665E-06
-3.704E-06	2.4828E-06	5.12E-06	2.1302E-06
-2.784E-06	1.8665E-06	2.1302E-06	5.7364E-06

Group	Predicted Frequency	Var. of Frequency	Coeff. of Variation	t-statistic	t 0.025	Degrees of Freedom	Confidence Interval Lower pt	Upper pt
L/H	0.01575	3.7342E-06	0.12269	8.15034	2.20099	11	0.01150	0.02000
P	0.01679	2.5535E-06	0.09516	10.50839	2.20099		0.01327	0.02031
P/L	0.01181	5.0087E-06	0.18951	5.27664	2.20099		0.00688	0.01674
Total Claims	221							

EXHIBIT 4

Risk	Report	Y	X
1	1	0	312.65
1	2	0	350.65
1	3	0	151.25
2	1	0	328.07
2	2	0	270.00
2	3	0	240.00
3	1	0	136.00
3	2	1	140.00
3	3	1	124.00
4	1	0	800.34
4	2	0	758.03
4	3	2	329.89
5	1	0	502.80
5	2	0	404.56
5	3	1	241.93
6	1	0	108.50
6	2	0	80.50
6	3	1	201.80
7	1	0	7.50
7	2	0	69.04
7	3	0	429.30
8	1	0	160.49
8	2	0	279.83
8	3	0	98.10
9	1	0	173.23
9	2	0	260.17
9	3	0	215.61
10	1	1	518.20
10	2	0	588.10
10	3	1	556.48
11	1	0	128.54
11	2	0	98.70
11	3	0	86.94
12	1	1	453.65
12	2	1	364.33
12	3	1	315.96
13	1	2	235.85
13	2	0	156.03
13	3	0	265.72
14	1	0	115.30
14	2	0	61.51
14	3	0	251.58
15	1	1	374.17
15	2	0	340.99
15	3	1	485.27
16	1	0	1353.45
16	2	0	1119.16
16	3	0	554.17
17	1	1	278.11
17	2	0	432.80
17	3	0	256.80
18	1	0	78.97
18	2	0	165.28
18	3	0	110.14
19	1	0	574.94
19	2	0	416.60
19	3	1	196.88
20	1	0	485.73
20	2	0	271.33
20	3	0	195.10
21	1	0	203.69
21	2	0	212.30
21	3	0	92.44
22	1	0	347.28
22	2	0	107.19
22	3	0	87.27

Var(e)	K
0.000942	5845.66

Var(A)	Degrees of Freedom
1.6116E-07	65

Risk	Zi	Weighted Average Frequency	μ	Credibility Weighted Frequency	Mod
1	0.122301	0.000000	0.000867	0.000761	0.88
2	0.125390	0.000000		0.000758	0.87
3	0.064045	0.005000		0.001132	1.31
4	0.244153	0.001059		0.000914	1.05
5	0.164303	0.000870		0.000868	1.00
6	0.062664	0.002559		0.000973	1.12
7	0.079641	0.000000		0.000798	0.92
8	0.084338	0.000000		0.000794	0.92
9	0.099930	0.000000		0.000780	0.90
10	0.221455	0.001203		0.000941	1.09
11	0.051005	0.000000		0.000823	0.95
12	0.162465	0.002646		0.001156	1.33
13	0.101119	0.003041		0.001087	1.25
14	0.068280	0.000000		0.000808	0.93
15	0.170368	0.001666		0.001003	1.16
16	0.341144	0.000000		0.000571	0.66
17	0.142031	0.001033		0.000891	1.03
18	0.057159	0.000000		0.000817	0.94
19	0.168952	0.000841		0.000863	1.00
20	0.140068	0.000000		0.000746	0.86
21	0.080016	0.000000		0.000798	0.92
22	0.084814	0.000000		0.000794	0.92
					1.00

B	Risk	A	Predicted Frequency	Coefficient of Variation	t-statistic	t 0.025	Confidence Interval Lower pt	Upper pt
0.000867	1	-0.000106	0.000761	0.565540	1.768220	1.997138	0.000000	0.001621
	2	-0.000109	0.000758	0.566302	1.765841	1.997138	0.000000	0.001616
	3	0.000265	0.001132	0.395768	2.526732	1.997138	0.000237	0.002026
	4	0.000047	0.000914	0.429760	2.326880	1.997138	0.000130	0.001698
	5	0.000001	0.000868	0.481326	2.077592	1.997138	0.000034	0.001702
	6	0.000106	0.000973	0.460730	2.170469	1.997138	0.000078	0.001868
	7	-0.000069	0.000798	0.555441	1.800370	1.997138	0.000000	0.001683
	8	-0.000073	0.000794	0.556516	1.796894	1.997138	0.000000	0.001676
	9	-0.000087	0.000780	0.560148	1.785244	1.997138	0.000000	0.001653
	10	0.000074	0.000941	0.424785	2.354132	1.997138	0.000143	0.001740
	11	-0.000044	0.000823	0.549078	1.821235	1.997138	0.000000	0.001725
	12	0.000289	0.001156	0.361709	2.764652	1.997138	0.000321	0.001991
	13	0.000220	0.001087	0.401858	2.488444	1.997138	0.000215	0.001959
	14	-0.000059	0.000808	0.552879	1.808715	1.997138	0.000000	0.001700
	15	0.000136	0.001003	0.414397	2.413147	1.997138	0.000173	0.001833
	16	-0.000296	0.000571	0.633215	1.579242	1.997138	0.000000	0.001294
	17	0.000024	0.000891	0.476477	2.098739	1.997138	0.000043	0.001738
	18	-0.000050	0.000818	0.550419	1.816797	1.997138	0.000000	0.001716
	19	-0.000004	0.000863	0.482365	2.073119	1.997138	0.000032	0.001694
	20	-0.000121	0.000746	0.569984	1.754434	1.997138	0.000000	0.001594
	21	-0.000069	0.000798	0.555527	1.800093	1.997138	0.000000	0.001683
	22	-0.000074	0.000794	0.556625	1.796541	1.997138	0.000000	0.001676

E(A) = -0.000022

A Note on the Paid Bornhuetter-Ferguson Loss Reserving Method: Recognizing Dependency on Case Reserves

Bruce E. Ollodart, FCAS, MAAA

A Note on the Paid Bornhuetter-Ferguson Loss Reserving Method:

Recognizing Dependency on Case Reserves

By

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Abstract

Many actuaries use a Bornhuetter-Ferguson ("BF") loss reserving method[1] based on paid loss data. What may be overlooked is that IBNR estimated with the paid BF method depends on both paid losses and case reserves, a situation the actuary may wish to avoid when case reserves are volatile or unreliable. This paper explores the dependence of IBNR estimates on case reserves when IBNR is derived from a paid loss Bornhuetter-Ferguson method. An alternative to reduce this dependence is provided.

Introduction

While revising a prior loss reserve study that utilized both paid and reported BF methods, the author noticed that the paid BF method is dependent on case reserves. The prior loss reserve study was based upon industry expected loss ratios and industry reporting and payment patterns. The revision to the study only affected the values for actual paid and reported (defined as paid loss plus case reserves) losses. The industry-based factors were not changed. Further, in both the original and revised versions, the author had selected an ultimate loss based on the average of the paid and reported BF methods. Upon review of the results, the author discovered an interesting result. What follows is a discussion of the author's findings, which should be of interest to those who use a paid BF method for estimating IBNR reserves.

[1] 1972, Bornhuetter, R.L. and Ferguson, R.E., "The Actuary and IBNR," PCAS LIX

Analysis

The easiest way to demonstrate the paid BF method's dependence on case reserves is through a simple example. For this example, reporting and payout patterns are based on industry wide data from Schedule P Other Liability. All other data was made up.

Exhibit I shows typical calculations utilizing the BF loss reserving method. The upper third of the exhibit is a paid BF method. The middle third of the exhibit is a reported BF method. In the paid method we estimate expected unpaid losses while in the reported method we estimate expected IBNR. Actual paid and reported losses are then added to expected amounts to derive estimates of ultimate loss for each method, respectively. In the lower third of the exhibit, the estimates of ultimate loss for each method have been averaged to arrive at a selected ultimate loss. Then reported losses are subtracted to calculate indicated IBNR.

Exhibit II shows the same calculation as Exhibit I using revised actual paid and reported losses. All other factors remain unchanged. The following table summarizes the results from Exhibit I and II:

	Exhibit I: Original	Exhibit II: Revised	Change
Paid Loss	141	144	3.0
Reported Loss	248	253	5.0
Selected Ultimate Loss	372	376	4.0
IBNR	124	123	-1.0
Case Reserve	107	109	2.0

What is interesting here is that the IBNR changed by minus one half of the change in case reserves.

Algebra helps explain what is happening in this example. In what follows, we assume that reporting patterns, payout patterns, and expected losses are not changed by revisions in the reported and paid data (we discuss certain implications of this assumption later). When the paid and reported BF methods are analyzed together, the author believes it is easier to compare the different contributions to the estimated IBNR resulting from each method. Therefore, we include weighting the paid BF method with the reported BF method in our analysis.

First, let us define the following symbols:

P_o = actual paid losses in the original data set
P_r = actual paid losses in the revised data set
R_o = actual reported losses in the original data set
R_r = actual reported losses in the revised data set
U = expected unpaid losses from paid BF method
I = expected IBNR losses from reported BF method
L_p = ultimate loss based on paid BF method
L_r = ultimate loss based on reported BF method
W = weight given to the paid method (1-W = weight given to reported method)
L = selected ultimate
IBNR = indicated IBNR based on subtracting reported losses from L

Using these symbols we can derive the following relationships:

For the **original** data set we have

$$L_p = U + P_o$$

$$L_r = I + R_o$$

$$\begin{aligned} L &= WL_p + (1-W)L_r \\ &= WU + WP_o + (1-W)I + (1-W)R_o \\ &= W(U + P_o - I - R_o) + I + R_o \end{aligned}$$

$$\begin{aligned} IBNR &= L - R_o \\ &= W(U + P_o - I - R_o) + I \end{aligned}$$

Similarly, for the **revised** data set we have

$$L = W(U + P_r - I - R_r) + I + R_r$$
$$IBNR = W(U + P_r - I - R_r) + I$$

If we then calculate the change in IBNR (ΔIBNR) equal to the revised IBNR minus the original IBNR, we have the following relationship:

$$\begin{aligned} \Delta IBNR &= W(U + P_r - I - R_r) + I - W(U + P_o - I - R_o) - I \\ &= W(P_r - R_r - P_o + R_o) \\ &= W[(R_o - P_o) - (R_r - P_r)] \qquad (1) \end{aligned}$$

The quantities in (1) inside the parentheses are the case reserves before and after the data was revised. The quantity in (1) inside the brackets represents the change in case reserves. Hence, the change in IBNR is equal to minus the change in case reserves times the weight W given to the paid method. That is, if ΔC is the change in case reserves, then

$$\Delta IBNR = -W\Delta C$$

In our example, W was ½ and ΔC was 2. The change in IBNR was -1.

What does this mean? The reported BF method explicitly produces an estimate of IBNR. To estimate IBNR using the paid BF method, we must subtract from expected unpaid losses an estimated amount for case reserves. It just happens that if we subtract actual reported loss from the paid BF ultimate loss, we use a "default" estimate of case reserves equal to the actual case reserves. *In essence, our estimate of IBNR made using the paid BF method is dependent on current case reserves.* This means that case reserves (including case reserve adequacy and volatility) become a factor in the IBNR derived by the paid BF method.

Exhibits III and IV demonstrate an alternative method to Exhibits I and II using the same original and revised data that was used above. The results from Exhibits III and IV are shown in the following table:

	Exhibit III: Original	Exhibit IV: Revised	Change
Paid Loss	141	144	3.0
Reported Loss	248	253	5.0
Selected Ultimate Loss	373	380	6.5
IBNR	125	127	1.5
Case Reserve	107	109	2.0

In Exhibits III and IV, an adjustment has been made to the paid BF method that substitutes expected reported losses for actual reported losses in the estimate of IBNR. We calculated the ultimate loss by adding the "alternative" IBNR, to the actual reported losses. Hence, when actual reported losses are subtracted from ultimate losses derived by this method, the alternative IBNR is the result.

The author's alternative method can be explained using algebra. By setting W to 1 for simplicity and examining only the paid BF method, we can derive the following IBNR formula for the alternative method:

$$\text{Original data set IBNR} = U + P_o - (1-I) \qquad (2)$$
$$\text{Revised data set IBNR} = U + P_r - (1-I) \qquad (3)$$
$$\Delta\text{IBNR} = P_r - P_o$$

The term "1-I" equals expected reported losses. The IBNR in (2) and (3) equals expected unpaid losses plus actual paid losses minus expected reported losses. This method develops an estimate of IBNR using paid losses and is independent of the current reported case reserves, as IBNR is now a function of the actual paid losses instead of case reserves. This may be a more desirable result in certain cases. For example, it gives the practitioner a method that eliminates direct dependence of IBNR on current case reserves when a paid BF method is used and current case reserves are unreliable.

The following points help put our findings in perspective:

1. Introducing reported loss information into the paid BF method in our alternative method may increase the correlation (if any) between the paid and reported methods. For example, by introducing the expected reported losses into the paid BF method, IBNR dependency on reported losses (and hence, case reserves) may still be present. In our example, the alternative paid BF method produces an answer closer to the reported BF method than the standard paid BF method.

2. In many situations, the reporting and payout patterns (and possibly the expected loss ratios as well) are derived from company data and can change as a result of revisions to reported and paid data. Hence, the relationships derived above would not be accurate, as U and I may change. In situations where data changes have modest impacts on the selection of loss development factors and expected loss ratios, the relationships derived above provide reasonable approximations. For example, where industry data is given significant weight in the selection of loss development factors, changes in U and I may be relatively small. Many actuaries use judgement in selecting payout and reporting patterns, and

minor changes to loss data will not affect those selections. Expected loss ratios may also be selected based on information independent of the company loss data currently under review.

3. Actuaries tend to utilize several methods to estimate IBNR in addition to the BF methods. Often, the resulting estimates of ultimate loss are averaged together or weighted in the process of selecting an ultimate loss. Much of the case reserve "dependency" effects noted in the above analysis may, for all practical purposes, be effectively decreased to a level that is reasonable. In most situations, case reserves may be reasonable and the standard paid BF method is fine. However, practitioners should be aware of the potential influence of case reserves on the paid BF method when it is used to derive IBNR, particularly in situations where it is the primary method used and case reserves are problematic. Careful selection of W and/or the use of the alternative paid BF method may provide alternatives in such a situation.

4. While our alternative to the standard paid BF method eliminates dependence of IBNR on current case reserves, dependence on current paid losses results. The practitioner should decide if this is a more appropriate method for the loss reserve data under review.

5. Using the standard paid BF method, an increase in case reserves results in a decrease in IBNR, as total unpaid losses are fixed at U. This method essentially allocates the total unpaid losses determined by U between IBNR and case reserves. Hence, increases in actual paid losses or actual case reserves have no effect on IBNR or reduce IBNR, respectively.

6. Using the alternative paid BF method, an increase in paid losses results in an increase in IBNR, as the ultimate loss increases, but the expected reported losses are fixed at "1-I". The alternative method responds directly to changes in paid losses, similar to the way the paid loss development method responds to changes in paid losses. Hence, increases in actual paid losses or actual case reserves increase IBNR or have no effect on IBNR, respectively.

7. For comparison, the reported BF method produces an estimate of IBNR that is independent of changes in current paid loss and/or case reserves.

Conclusion

The standard paid BF method uses expected unpaid losses and *actual* case reserves to estimate IBNR. This compares to the reported BF method that estimates IBNR based on expected losses and expected reporting patterns. Hence, IBNR derived by the standard paid BF method is dependent on case reserves. Case reserve dependency in the paid BF method can be eliminated by subtracting expected reported losses, instead of actual reported losses, from the standard paid BF ultimate loss to estimate IBNR. This adjustment results in IBNR that is dependent on paid losses instead of case reserves. In certain cases, the actuary may prefer IBNR estimates that are dependent on paid losses rather than case reserves, particularly if case reserves are volatile or unreliable.

Acknowledgment

The author would like to thank Mr. Raymond S. Nichols, FCAS, MAAA, for his assistance in reviewing this paper and recommending changes to the earlier drafts.

Estimates Using Standard BF Approaches
Other Liability - Original Data

Exhibit I

Paid BF Approach								
Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Payout Pattern	Unpaid Percentage	Estimated Unpaid Loss	Actual Paid Loss	Estimated Ultimate Loss
12	106	0.70	74	0.099	0.901	67	8	75
24	105	0.75	79	0.238	0.762	60	15	75
36	100	0.66	66	0.403	0.597	39	28	67
48	110	0.68	75	0.556	0.444	33	37	70
60	115	0.70	81	0.675	0.325	26	53	79
Total	536		374			226	141	367

Reported BF Approach								
Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Report Pattern	*IBNR* Percentage	Estimated IBNR Loss	Actual Reported Loss	Estimated Ultimate Loss
12	106	0.70	74	0.327	0.673	50	26	76
24	105	0.75	79	0.548	0.452	36	45	81
36	100	0.66	66	0.705	0.295	19	48	67
48	110	0.68	75	0.811	0.189	14	56	70
60	115	0.70	81	0.875	0.125	10	73	83
Total	536		374			129	248	377

BF Approach Selected Ultimate Loss and Estimated IBNR					
Months Maturity	Paid BF Method	Reported BF Method	Selected Ultimate*	Reported Losses	Indicated IBNR
12	75	76	75	26	49
24	75	81	78	45	33
36	67	67	67	48	19
48	70	70	70	56	14
60	79	83	81	73	8
Total	367	377	372	248	124

*Average of paid and reported methods

Exhibit II

Estimates Using Standard BF Approaches
Other Liability - Revised Data

Paid BF Approach								
Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Payout Pattern	Unpaid Percentage	Estimated Unpaid Loss	Actual Paid Loss	Estimated Ultimate Loss
12	106	0.70	74	0.099	0.901	67	10	77
24	105	0.75	79	0.238	0.762	60	13	73
36	100	0.66	66	0.403	0.597	39	29	68
48	110	0.68	75	0.556	0.444	33	38	71
60	115	0.70	81	0.675	0.325	26	54	80
Total	536		374			226	144	370

Reported BF Approach								
Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Report Pattern	IBNR Percentage	Estimated IBNR Loss	Actual Reported Loss	Estimated Ultimate Loss
12	106	0.70	74	0.327	0.673	50	28	78
24	105	0.75	79	0.548	0.452	36	44	80
36	100	0.66	66	0.705	0.295	19	49	68
48	110	0.68	75	0.811	0.189	14	55	69
60	115	0.70	81	0.875	0.125	10	77	87
Total	536		374			129	253	382

BF Approach Selected Ultimate Loss and Estimated IBNR					
Months Maturity	Paid BF Method	Reported BF Method	Selected Ultimate*	Reported Losses	Indicated IBNR
12	77	78	77	28	49
24	73	80	76	44	32
36	68	68	68	49	19
48	71	69	70	55	15
60	80	87	84	77	7
Total	370	382	376	253	123

*Average of paid and reported methods

Exhibit III

Estimates Using Adjusted BF Approaches
Other Liability - Original Data

Paid BF Approach

Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Payout Pattern	Unpaid Percentage	Estimated Unpaid Loss	Actual Paid Loss	Cumulative Reporting Pattern	Expected Reported Loss	Actual Reported Loss	Estimated Ultimate Loss*
12	106	0.70	74	0.099	0.901	67	8	0.327	24	26	77
24	105	0.75	79	0.238	0.762	60	15	0.548	43	45	77
36	100	0.66	66	0.403	0.597	39	28	0.705	47	48	69
48	110	0.68	75	0.556	0.444	33	37	0.811	61	56	66
60	115	0.70	81	0.675	0.325	26	53	0.875	70	73	82
Total	536		374			226	141		245	248	370

Reported BF Approach

Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Report Pattern	IBNR Percentage	Estimated IBNR Loss	Actual Reported Loss	Estimated Ultimate Loss
12	106	0.70	74	0.327	0.673	50	26	76
24	105	0.75	79	0.548	0.452	36	45	81
36	100	0.66	66	0.705	0.295	19	48	67
48	110	0.68	75	0.811	0.189	14	56	70
60	115	0.70	81	0.875	0.125	10	73	83
Total	536		374			129	248	377

BF Approach Selected Ultimate Loss and Estimated IBNR

Months Maturity	Paid BF Method	Reported BF Method	Selected Ultimate**	Reported Losses	Indicated IBNR
12	77	76	76	26	50
24	77	81	79	45	34
36	69	67	68	48	20
48	66	70	68	56	12
60	82	83	82	73	9
Total	370	377	373	248	125

* Expected unpaid loss + actual paid loss - expected reported loss + actual reported loss

**Average of paid and reported methods

Estimates Using Adjusted BF Approaches
Other Liability - Revised Data

Exhibit IV

Paid BF Approach

Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Payout Pattern	Unpaid Percentage	Estimated Unpaid Loss	Actual Paid Loss	Cumulative Reporting Pattern	Expected Reported Loss	Actual Reported Loss	Estimated Ultimate Loss*
12	106	0.70	74	0.099	0.901	67	10	0.327	24	28	81
24	105	0.75	79	0.238	0.762	60	13	0.548	43	44	74
36	100	0.66	66	0.403	0.597	39	29	0.705	47	49	71
48	110	0.68	75	0.556	0.444	33	38	0.811	61	55	66
60	115	0.70	81	0.675	0.325	28	54	0.875	70	77	87
Total	536		374			226	144		245	253	378

Reported BF Approach

Months Maturity	Earned Premium	Expected Loss Ratio	Expected Loss	Cumulative Report Pattern	IBNR Percentage	Estimated IBNR Loss	Actual Reported Loss	Estimated Ultimate Loss
12	106	0.70	74	0.327	0.673	50	28	78
24	105	0.75	79	0.548	0.452	36	44	80
36	100	0.66	66	0.705	0.295	19	49	68
48	110	0.68	75	0.811	0.189	14	55	69
60	115	0.70	81	0.875	0.125	10	77	87
Total	536		374			129	253	382

BF Approach Selected Ultimate Loss and Estimated IBNR

Months Maturity	Paid BF Method	Reported BF Method	Selected Ultimate**	Reported Losses	Indicated IBNR
12	81	78	79	28	51
24	74	80	77	44	33
36	71	68	70	49	21
48	66	69	67	55	12
60	87	87	87	77	10
Total	378	382	380	253	127

* Expected unpaid loss + actual paid loss - expected reported loss + actual reported loss
**Average of paid and reported methods